YouNiverse: Large-Scale Channel and Video Metadata from English-Speaking YouTube

Manoel Horta Ribeiro, Robert West
EPFL

Abstract

YouTube plays a key role in entertaining and informing people around the globe. However, studying the platform is difficult due to the lack of randomly sampled data and of systematic ways to query the platform’s colossal catalog. In this paper, we present YouNiverse, a large collection of channel and video metadata from English-language YouTube. YouNiverse comprises metadata from over 136k channels and 72.9M videos published between May 2005 and October 2019, as well as channel-level time-series data with weekly subscriber and view counts. Leveraging channel ranks from socialblade.com, an online service that provides information about YouTube, we are able to assess and enhance the representativeness of the sample of channels. YouNiverse, publicly available at https://doi.org/10.5281/zenodo.4327607, will empower the community to do research with and about YouTube.

1 Introduction

YouTube plays an important role in society. In 2018, 54% of adult U.S. users said the platform was somewhat or very important for helping them understand what is happening in the world [26]. The role of the platform is also by no means limited to the United States [31]: attracting content creators that range from prolific music labels in India [13] to reactionary influencer-politicians in Brazil [17].

Given the sheer size of the platform’s catalog and the multimedia nature of its content, systematically finding content on YouTube is hard. Thus, when researchers study the platform, they resort to a variety of heuristics such as using the Website’s search functionality [22], snowball sampling recommendations [21], and selecting links that are shared in other platforms (e.g., Twitter [34]). These sampling strategies involve a great amount of extra work and often hinder the generalizability of studies (since research is carried with little knowledge about the representativeness of the data analyzed).

While the role of YouTube in our lives is increasing, recent moves by platforms limiting access to data through Application Programming Interfaces (APIs) exacerbate data collection challenges [9]. In this context, hoping to foster research on the platform, in this paper we present YouNiverse a large dataset of channel and video metadata from English-speaking YouTube. To the best of our knowledge, this dataset represents the largest collection of YouTube metadata made publicly available.

The dataset is composed of: 1) channel metadata for over 136k channels, including their number of subscribers, videos, and join date; 2) video metadata for over 72.9M videos, including description, number of likes, views, etc.; 3) for most of the channels (> 98%), additional time series data depicting the number of subscribers and views they had on a weekly granularity (2.8 years of data per channel on average); 4) channel-level weights to partially control for the dataset’s sampling biases.

2 Dataset Collection and Preprocessing

Besides YouTube itself, we crawl data from two third-party sources that aggregate YouTube metadata: 1) channelcrawler.com, a website that compiles YouTube channels and makes them searchable through a variety of criteria [2]. The website exists can be traced back to mid-2014 and uses a snowball sampling approach to collect channels; 2) socialblade.com, a website that tracks social media statistics and analytics [4]. The website has existed since 2008 and originally tracked statistics for digg.com. In 2010, they switched their focus to tracking YouTube statistics [3] and have since added other platforms such as Twitch.tv and Instagram. In 2014, the company launched consulting and channel management services to help content creators and companies that want to advertise on them [5]. We illustrate the sources and the data collection and processing methodology in Fig. 1.

2.1 Step 1: Collection

Channel metadata. We gathered a pool of 156,978 channels by crawling all English channels with more than 10k subscribers and 10 videos from channelcrawler.com. Data collection took place between 2019-09-12 and 2019-09-17. Language classification was made by the website using an automatic classifier. Their repository is particularly helpful as channelcrawler.com, a website that compiles YouTube channels and uses a snowball sampling approach to collect channels; 2) socialblade.com, a website that tracks social media statistics and analytics [4]. The website has existed since 2008 and originally tracked statistics for digg.com. In 2010, they switched their focus to tracking YouTube statistics [3] and have since added other platforms such as Twitch.tv and Instagram. In 2014, the company launched consulting and channel management services to help content creators and companies that want to advertise on them [5]. We illustrate the sources and the data collection and processing methodology in Fig. 1.

Additionally, we crawled additional metadata from subscriber rankings for each of the channels from socialblade.com, which order channels according to how many subscribers they had. For example, if a channel’s subscriber rank equals 10, this
means that, among channels tracked by socialblade.com, there are only 9 channels with a higher number of subscribers. As we discuss further in Section 6, this allows us to assess the representativeness of our channel sample and possibly enhance it by weighting channels when performing data analysis.

Video metadata. For all 156,978 channels obtained from channelcrawler.com, we downloaded the metadata for all their available videos from YouTube. In total, we crawled over 84M videos between 2019-10-29 and 2019-11-23.

Channel time-series. Lastly, we compiled time-series related to each channel. These come from a mix of YouTube data and from time-series crawled from socialblade.com. From the former, we derived a weekly time-series indicating how many videos each channel posted per week. From the latter, we crawled weekly statistics on the number of viewers and subscribers per channel. This data was available for around 153k of the channels.

2.2 Step 2: Filtering

Although channelcrawler.com automatically classifies the languages of each channel, we found that many of the channels posted most of their content in Hindi or Russian. In this context, to ensure the consistency of our dataset we additionally filtered channels using langdetect [29]. For each channel, we appended the titles and descriptions for 10 random videos in the dataset and accepted those predicted to be in English with probability >60%. This reduced our channel pool to 136,470 and our video pool to 72,924,794.

2.3 Ethics

We collect only data publicly available on the Web and did not (1) interact with online users in any way, nor (2) simulate any logged-in activity on YouTube or the other platforms. Data was only collected for channels with a significant number of followers (>10k) which had previously been collected and made searchable by other third-party applications.

3 Dataset Description

Our dataset consists of three files which we describe below.

Video metadata. (df_videos_en.jsonl.gz): Metadata associated with the 72,924,794 videos. This includes videos from all 136,470 channels. Metadata made available include: the category of channels (self-defined when they upload a video to YouTube), channel and video ids, upload date, number of likes, dislikes, and views, duration in seconds, textual description, and self-assigned tags. Importantly, these data is obtained at crawl time (between 2019-10-29 and 2019-11-23) which is also provided as a field.

Channel metadata. (df_channels_en.csv.gz): Metadata associated with the 136,470 channels: channel id, join date, country, number of subscribers, most frequent category, as well as the channel’s position in socialblade.com’s subscriber ranking. Number of subscribers is provided both as crawled from channelcrawler.com (between 2019-09-12 and 2019-09-17), and as crawled from socialblade.com (2019-09-27). Additionally, we also provide a set of weights (derived from socialblade.com’s subscriber rankings) that can be used to partially correct sample biases in our dataset (see Sec. 6).

Time-series data. (df_timeseries_en.csv.gz): Time-series data on channel activity on a weekly granularity. The span of each time-series vary on a channel-level basis depending on when they socialblade.com started tracking them. On average it contains 2.8 years of data per channel for 133k channels (notice that this means there are roughly 4k channels for which there is no time-series data). Each data point includes the number of views and subscribers obtained in the given week, as well as the number of videos posted by the channel. The number of videos is calculated using the video upload dates in our video metadata, therefore, videos that were unavailable at crawl time were not be accounted for. We provide a brief characterization of the coverage of the time-series data in Sec. 5.
Top 5% = 82
Top 5% = 70
Top 5% = 41
YouNiverse conforms with the FAIR principles. It is
We provide a quantitative overview of the dataset, describing
Figure 2: Distributions of video and channel statistics. Using both a box-plot and a histogram, we depict log-transformed distributions of
video and channel statistics present on video metadata (Views, Likes, Dislikes, and Duration), channel metadata (Videos per channel, Subscribers
per channel), and time-series data (Weekly views gain, Weekly subscriber gain). For the box-plot, box boundaries mark quartiles, the middle
bar the median, and whiskers depict the 5th and the 95th percentile. Above each plot, we report what percentage of the sum of each statistic is
concentrated in the top 5% of data points, as well as the range of values taken by the top 5% (with the solid line).

4 Compliance with FAIR Principles
YouNiverse conforms with the FAIR principles. It is findable
since it is made publicly available via Zenodo. It is accessible
since it can be accessed by anyone in the world and since it
leverages standard data formats (.csv, .json, .gz). It is interoperable as almost every programming language has
libraries that allow individuals to work with data in formats employed. It is reusable as it is richly described in this paper.

5 Dataset Characterization
We provide a quantitative overview of the dataset, describing
the data and assessing its completeness.

Video and channel statistics. Figure 2 presents the log-
transformed distribution of several video and channel statistics.

In the top row, we show statistics derived from video-level
metadata. Using an histogram and a box-plot, we depict the distributions of the number of views, likes, dislikes, and of how
long videos last. Notice that the video duration distribution is
bi-modal, with a peak around $2^{2.25}$ ($\approx 3$ minutes) and another around $2^{5.75}$ ($\approx 10$ minutes). The second peak may be explained
by a threshold set by YouTube, where content creators would only be able to place multiple ads if a video was longer than 10
minutes [2]. Recently, in July 2020, YouTube has changed the
minimum duration required, which is now 8 minutes [6].

In the bottom row, we depict both channel-level statistics
(in the first two columns, from channelcrawler.com data), and
time series related statistics (in the last two columns, from
socialblade.com data). We note that there is a high number
of weeks for which the weekly gain of views and subscribers equals zero ($\sim 2\%$ of view data points, and $\sim 8\%$ of of sub-
scribers data points). While these may be due to data collection
or corrections done by socialblade.com, we find that most of
the missing data points for subscriber data are associated chan-
nels with close to 10 thousand subscribers. More specifically,
around 76\% of missing data points belong to channels that
had between 9,900 and 10,100 users. We believe this could
be indicative of YouTubers artificially boosting their channels
towards the 10 thousand follower mark (and subsequently not
gaining any additional subscribers).

On top of the box-plot associated with each statistic, we draw
a line showing the range of values taken by the top 5% data points. Above the line, we also write what percentage of the
sum of all values belongs to the top 5% data points. We find that some of these statistics are heavily concentrated for
top videos and channels. For example, we find that the videos
with the top 5% most views are responsible for 85.2\% of all views (in accordance to previous work [10,27]).

Aggregated video statistics. Table 1 shows the total number of
views, videos, likes, and duration for each of the 15 categories
provided by the platform. We find that Music and Entertainment are the most popular categories ($\geq 2000B$ views each), while
the gaming category contains the most videos ($\sim 13.7M$ videos).
Gaming videos are also substantially longer than those in other
categories: while the $12.3M$ videos in the entertainment cate-
gory span around 243 years, the $13.7M$ Gaming videos would
last for more than 600 years.

https://bit.ly/3gPfuUN
Table 1: Total number of views, videos, likes and video duration in each category in our dataset. We omit videos belonging to

| Categories        | # Views (Billion) | # Videos (Millions) | # Likes (Millions) | Duration (Years) |
|-------------------|-------------------|---------------------|--------------------|------------------|
| Autos & Vehic.    | 123.1             | 2.3                 | 956.3              | 27.0             |
| Comedy            | 345.0             | 1.2                 | 6134.2             | 18.9             |
| Education         | 502.4             | 3.8                 | 2881.4             | 117.1            |
| Entertainment     | 2287.7            | 12.3                | 20140.6            | 243.1            |
| Film & Animation  | 576.3             | 2.4                 | 3737.8             | 47.7             |
| Gaming            | 1042.5            | 13.7                | 17351.3            | 623.2            |
| Howto & Style     | 420.7             | 4.0                 | 5790.8             | 73.6             |
| Music             | 2475.0            | 8.3                 | 19270.5            | 124.1            |
| News & Politics   | 158.6             | 8.9                 | 1892.9             | 144.8            |
| Nonprofits        | 18.5              | 0.8                 | 242.9              | 29.5             |
| People & Blogs    | 617.3             | 6.9                 | 9138.1             | 148.8            |
| Pets & Animals    | 72.1              | 0.6                 | 659.8              | 9.9              |
| Science & Tech.   | 175.0             | 2.4                 | 1978.4             | 47.5             |
| Sports            | 262.0             | 4.4                 | 2528.1             | 77.3             |
| Travel & Events   | 56.4              | 1.1                 | 459.8              | 19.2             |
| Total             | 9132.7            | 72.9                | 93162.9            | 1751.8           |

Video and channel creation dates. Figure 3 shows the creation dates of videos and channels in the dataset in both relative and absolute terms. We find that the around 50% of channels in the dataset were created after 2014, and around 50% of videos were created since 2018. The fact that videos are more recent could be due YouTube’s steady growth over the years. However, it is worth noticing that older channels and videos may have been deleted by content creators, or taken down by copyright complaints, which could induce a recency bias in our video sample.

Time series completeness. Notice that not all channels have the exact same time series data available. We characterize the completeness of our data across the years in Figure 4. For each date, shown in the x-axis, we show the percentage of channels that had been already created for which we have time series data available. Starting in late 2016, most of the channels (∼80%) have time series data available. We additionally illustrate the time series data made available with three randomly sampled channels in Figure 5 depicting the cumulative number of views, subscribers and videos of each channel through their whole lifespan.

Estimating representativeness through ranks. In Figure 6 (left), we explore socialblade.com rankings to get a sense of how representative our data is compared to socialblade.com. We find that for top 10k channels, we have around 35% of all channels present in socialblade.com subscriber ranking, and that for the top 100k, around 25%. As a sanity check, we additionally study the relationship between the subscriber ranks provided by socialblade.com and the actual number of subscribers each channel has (obtained from channelcrawler.com). Although there are discrepancies between the two, we find very high correlation (Spearman’s ρ < −0.99).

Figure 3: Temporal distribution of the creation of channels and videos. Cumulative number of videos and channels created in each point in time from 2004 to 2019 (left), as well as these values normalized by the total number of videos and channels (right).

Figure 4: Time series completeness. Monthly percentage of channels for which there is time series data. Notice that we plot, for each value in the x-axis, the percentage of channels that were already created for which there is time-series data available.

Figure 5: Time series examples. For three channels selected at random (channel ids above each plot), we depict the cumulative number of views, subscribers and videos.

Figure 6: Ranking completeness. On the left-hand side, we depict, for each subscriber rank present in the sample, the percentage of channels present in our sample up to that ranking. For example, if we had in our sample the channels corresponding to rankings 3, 5 and 10, we would have probabilities 1/3 up to the 3rd ranking, 2/5 up to the 5th ranking, and 3/10 up to the 10th. On the right-hand side we depict the relationship between subscribers rank (obtained from socialblade.com) and number of subscribers (obtained from channelcrawler.com).
### 6 Correcting for Sampling Bias

Figure 6 shows that our sample is biased towards channels that rank higher in socialblade.com’s subscriber rank. In this section we discuss how we can account for this bias in subsequent analyses by giving more weight to channels that are under-represented in the sample.

Let $L$ be an array containing the socialblade.com rankings for channels in our sample ordered. For a given channel corresponding to the position $i$ in this list, and an odd-valued window of size $k = 2m + 1$, its local sampling probability is

$$PS(i,m) = \frac{2m + 1}{L[i + m] - L[i - m] + 1}.$$  

Which in practice means that we estimate what percentage of channels between $L[i + m]$ and $L[i - m]$ we have in our sample. Finally, to estimate the weight, we simply take the inverse of the local sampling probability: $w_{i,m} = PS(i,m)^{-1}$.

We illustrate this procedure in Fig. 7 but the rationale is simple: while the probability of sampling channels of different ranks is clearly not homogeneous globally, we can estimate the local probabilities and assign to channels weights inverse to those probabilities. In our described method, the size of the window controls how local is the sampling probability.

Choosing the window size $k$. An unsolved issue with the proposed method is how to determine window size. A too small window size may create noisy weights, while a too large one may defeat the purpose of the method altogether (after all, the whole point is to control for local differences in sampling probability). To empirically determine a good window size, we experiment with a wide range of values $^6$ and pick smallest value for which we find the time-series to be well-behaved w.r.t. noise ($k = 2000$). We illustrate weights for three different values of $k$ in Figure 8(a).

Example usage. We provide a concrete example of how one can use these weights for to obtain statistics more representative of YouTube as a whole. Suppose for instance that we want to estimate the average number of videos per channel in YouTube. If we naively take the average of our sampled channels we find that $\mu = 699.78$. However, notice that channels in top ranks have on average many more videos, as shown in Figure 8(a). Thus, since these channels are much more likely to be in the sample, we are over-estimating the average number of channels. Fortunately we can correct for our bias calculating the weighted average, finding $\mu = 559.26$. Interestingly, we find little variation from the different window sizes in this estimate, for example, for $k = 100$, we find $\mu = 555.53$, and for $k = 32000$, we find 578.09.

Limitation of the correction scheme. It is important to notice that our dataset focus on English-speaking YouTube channels, while the subscriber rank is language agnostic. This implies that we could use this sample to deduce information about YouTube in general. However, when doing so, are likely to

---

$^6$k $\in\{50, 100, 250, 500, 1000, 2000, 4000, 8000, 16000, 32000\}$

---

Figure 7: Weighting scheme. Suppose that we are assigning weights to 3 channels we have in our sample: #14, #16 and #17 using a window size $k = 3$. This means that when assigning a channel its weight, we look for the first ($m = 1$) channel in the sample before and after the channel at hand. So, for channel #14, if we have channels #12 and #16 in the sample but not #13 or #15, we would have that $PS(#14|k = 3) = 3/(16 - 12 + 1) = 3/5$. More intuitively, as the figure and the name suggest, this is the inverse of the percentage of channels sample in this window. If the window around a channel has more sampled channels (e.g., for #16) the weight will be smaller, while if the sample has fewer (e.g., for #17), the weight will be bigger.

Figure 8: Weights in practice. In (a), we depict the how of our weighting scheme assigns weights to channels of different subscriber rankings. In (b), we depict a moving average over the rankings (window size = 1000) that calculates, at each step, the average number of videos per channel. Two horizontal lines depict the average value with and without the weight adjustment.
over-emphasize features associated with English speaking channels. For example, if we try to estimate the average number of videos per channel in all of YouTube using only our sample, and if it happens that the average number of videos per channel for English-speaking channels is smaller than the for other languages, we may underestimate the statistic. Moreover, this methodology presupposes that socialblade.com rankings are complete and correct. Regardless of these limitations, we argue that this method is far superior to what has been done in previous work (which we extensively review in the next section), where the representativeness of the data is often neither considered nor assessed.

7 Related Work

We review previous studies using YouTube data with an emphasis on their data collection efforts. We emphasize work that has made their data available and that tried to broadly characterize YouTube quantitatively.

Background on YouTube

YouTube is an online video-sharing platform created in 2005 and that has since emerged as a dominant social media service[27]. The platform allows anyone to upload online videos, as well as to interact with videos uploaded by others. In 2020, Google for the first time disclosed 15 billion dollar earnings associated with the platform[32], which they had bought in 2006.

Performance-oriented characterizations. Large scale characterizations analyzing YouTube date from 2007. Back then, in the early years of Web 2.0, the main interest was to characterize content creation and consumption patterns in the platform, often with a focus in enhancing the service quality performance-wise[19,20,37]. In this direction, we highlight the works of Cha et al.[11] and of Cheng et al.[12] which characterized YouTube in terms of how much content was produced and consumed in the platform, comparing statistics with other Video-on-Demand systems. In both cases, authors identified patterns in the creation and consumption of videos that could be leveraged to enhance service quality.

The two papers employ different data collection methodologies. Cha et al.[11] crawled and analyzed the “Entertainment” and “Science and Technology” categories, which had nearly 2 million videos altogether. When data for the paper was collected, YouTube had pages indexing all videos that belonged to a given category, which made data collection viable. Cheng et al.[12] performed a four-month crawl collecting metadata for over 3 million YouTube videos, using a breadth-first search to find videos from recommendations in the platform.

As the platform grew and challenges related to its infrastructure increased, performance-oriented analyses of the website would continue to be an active area of research[16,25,28]. Of this subsequent work, of particular relevance is the method developed by Zhou et al.[35] to obtain an unbiased sample of YouTube videos via random prefixes. They leverage a feature of the search API where one could match the prefix of video ids by using queries like watch?v=xyz. Their analysis estimated that there were around 500 million YouTube videos at the time of the research, and shed light on the bounds for the total storage YouTube must have had, as well as the network capacity needed to deliver videos.

Virality and engagement. Previous research has also leveraged YouTube data to characterize the dynamics of virality in the platform, as well as to better understand which factors (content-related or not) make videos popular.

Figueiredo et al.[15] characterize the popularity growth of YouTube videos over time. Leveraging a deprecated feature that allowed to extract time-series data for statistics such as ratings and views, they collected data associated with over 150 thousand unique videos from YouTube top lists, the YouTomb project[6] and from using the search functionality with random topics obtain from a lexical ontology. They found that popularity growth patterns to be largely dataset-reliant. For example, while videos in the top lists experience sudden bursts of popularity throughout their lifetime, copyright protected videos get most of their views earlier in their lifespan.

In a similar vein, Borghol et al.[7] studied the popularity dynamics of user-generated videos leveraging data obtained from sampling recently upload videos and videos obtained through keyword searches, finding significant differences from results between the two samples. In subsequent work[6], they crawled a large dataset of 48 sets of identical or nearly identical videos on YouTube (1761 videos overall) to study content-agnostic factors that impact YouTube video popularity. They found a strong linear “rich-get-richer” behavior, with the total number of previous views being the most important factor for predicting which videos would gain views.

Brodersen et al.[8] study the relationship between popularity and locality of online YouTube videos, finding that, despite the global nature of the Web, video consumption is largely constrained by geographic locality. The paper, authored by Googlers, leverages a random sample of 20 million YouTube videos uploaded between September 2010 and August 2011.

Abisheva et al.[1] analyze cross-platform interactions between YouTube and Twitter, analyzing video-sharing events. Their dataset comprises 5.6 million YouTube videos and over 15 million video-sharing events from around 87 thousand Twitter users. Among other things, their findings suggest a superlinear relationship between initial video success on Twitter and final success on YouTube.

Wu et al.[34] studied whether engagement in online videos could be predicted. Authors define a new metric, relative engagement, which they found to be strongly correlated with recognized notions of quality. To obtain the data for this study, the authors developed a crawler to collect three daily time-series related to video attention dynamics: the volume of shares, view counts, and watch time (leveraging the same feature as[15]). They analyzed two datasets: a collection of over 5.3M videos published between 2016-07-01 and 2016-08-31 from around 1M channels collected from Twitter’s streaming API, as well as over 96 thousand videos from high-quality sources.

[^9]: An MIT initiative to monitor videos removed due to copyright violations in YouTube.
Platform features. Several other studies collect YouTube data to understand the impact or the usage of specific features, such as comments, ads, and recommendations.

Benevenuto et al. [5] studied “response videos,” a now deprecated system where anyone could respond to a YouTube video with a video of their own. The response video would then be tagged along with the “responded” video. Analyzing around 196k YouTube users, 224k “responded” videos, and 418k video “responses,” they found evidence of opportunistic behavior such as self-promotion and spamming.

Zhou et al. [36] studied the impact of the recommender system on video views, finding that recommendations are the main source of views for the majority of the videos on YouTube. Leveraging the same deprecated feature as Figueiredo et al. [15], they analyzed around 700 thousand videos collected: 1) via the API, or 2) by capturing and parsing video requests at a university network gateway.

Siersdofer et al. [30] present an in-depth study of commenting on YouTube. They analyze the relationship between comment and views and train a classifier capable of predicting the community’s acceptance of a given comment. Authors analyze 6 million comments on 67 thousand YouTube videos obtained through the website’s search functionality.

Arantes et al. [4] leverage logs of HTTP requests from a large university to study ad consumption on YouTube. Their dataset comprises over 99 thousand video-ad exhibitions, 5.6 thousand unique ads, and 58 thousand unique videos. Their analysis found the fraction of ad exhibitions that are streamed until completion to be high (~29%) relative to traditional online advertisement (where click-through rates are below 0.01%).

Other characterizations. Recent studies have again tried to provide overall characterizations of YouTube. We highlight two recent papers in this direction. Bärtl [10] has obtained a sample of around 8M videos belonging to approximately 20k channels through randomly searching for keywords, and Rieder et al. [27] have performed what is perhaps the largest study characterizing YouTube, analyzing static metadata of over 36 million channels and 700 million videos. Both these studies provide high-level statistical analyses finding, for example, that the vast majority of views goes to a small minority of channels (which, perhaps ironically, was also a conclusion of Cha et al. [11] over a decade before).

Other studies. So far, we have discussed attempts to broadly characterize YouTube, its features, and the dynamics of virality in the platform. These are the most relevant previous work to contextualize the contribution provided by our dataset. However, it is worth stressing that previous work has also explored problematic phenomena in the platform such as self-promotion and spamming.

Table 2: Comparison between the dataset here presented and other datasets made available in previous work. Notice that, for brevity’s sake, we report dataset size only in number of videos.

| Kind of data                          | Dataset size | Sampling strategy                                                                 |
|---------------------------------------|--------------|-----------------------------------------------------------------------------------|
| Video metadata                        | ~2M videos   | Crawled YouTube categories “Entertainment” and “Science and Technology.”          |
| Video metadata                        | ~3M videos   | Multiple BFS crawls done between March 5th and April 16th 2007.                  |
| Video metadata                        | ~1.2M videos | Recently uploaded videos + keyword search                                        |
| Video metadata + video sharing events | ~5.6M videos | Extracted videos from 28h of all public tweets containing URLs                   |
| Video metadata                        | ~5.3M videos | Twitter Stream API (between July 1st and August 31st + high quality sources      |
| Video metadata                        | ~8M videos   | Keyword search                                                                    |
| Video metadata + channel metadata + popularity time-series | ~85M videos | Crawled websites that publicly display statistics about YouTube.      |

8 Discussion and conclusion

In this last section, we briefly compare our dataset with existing large-scale YouTube related data that is publicly available. Additionally, we discuss a couple of research directions where we think this data may be particularly useful.

Relationship between this and prior work. We briefly discuss the relationship between the dataset here presented and the data previously used by researchers to better understand YouTube. We focus our comparison with other datasets that were made publicly available in previous work and depicted in Table 2. Compared to previously available data, our dataset is:

- **Channel-driven.** For each channel, we collect metadata and popularity time series along with all available videos. Other recent datasets focus largely on obtaining representative video samples [10][34]. Our approach is particularly interesting to study the process of content creation on YouTube (since our dataset has, for each channel, all videos available at the crawl time).
We would like to thank Richard Patel for the useful insights in which channels grow and professionalize themselves is key to starting point.

References

We would like to thank Richard Patel for the useful insights in which channels grow and professionalize themselves is key to starting point.

Possible use cases. We believe this dataset can foster research on YouTube in a variety of ways. First, it may help researchers to quantitatively study the evolution of content creation in the platform throughout the years. As “digital influencers” become increasingly important in the public debate, studying the way in which channels grow and professionalize themselves is key to better understand our current information ecosystem. Second, the dataset may help to study the evolution of content itself on YouTube. Since its creation, the “rules of the game” have changed several times in the platform, and video metadata enables us to capture many of these transformations (e.g. what are the ideal video lengths throughout the years?). Lastly, this dataset can be a useful resource to a variety of more focused studies. As discussed, previous work often resort to simple heuristics to find channels or videos related to specific topics (e.g. cancer), and our dataset may act as a comprehensive starting point.

References

We would like to thank Richard Patel for the useful insights in all things related to crawling.

Large. Our dataset is an order of magnitude larger than the other recent publicly available YouTube dataset [10]. This is particularly important due to the heterogeneity of YouTube.

Recent. Unlike most previous comprehensive large scale datasets [11][12], our dataset contains data from more recent years, where problematic phenomena in YouTube, such as troublesome children content [25] or fringe content [21], gained the spotlight. We hope that this data enables the better contextualization of such content amidst the broader YouTube context.

Possible use cases. We believe this dataset can foster research on YouTube in a variety of ways. First, it may help researchers to quantitatively study the evolution of content creation in the platform throughout the years. As “digital influencers” become increasingly important in the public debate, studying the way in which channels grow and professionalize themselves is key to better understand our current information ecosystem. Second, the dataset may help to study the evolution of content itself on YouTube. Since its creation, the “rules of the game” have changed several times in the platform, and video metadata enables us to capture many of these transformations (e.g. what are the ideal video lengths throughout the years?). Lastly, this dataset can be a useful resource to a variety of more focused studies. As discussed, previous work often resort to simple heuristics to find channels or videos related to specific topics (e.g. cancer), and our dataset may act as a comprehensive starting point.

References

We would like to thank Richard Patel for the useful insights in all things related to crawling.

References

[1] A. Abisheva, V. R. K. Garimella, D. Garcia, and I. Weber. Who watches (and shares) what on youtube? and when?: using twitter to understand youtube viewership. In Proceedings of the 7th ACM international conference on Web search and data mining - WSDM ’14, pages 593–602, New York, New York, USA, 2014. ACM Press.

[2] J. Alexander. YouTube is finally letting creators know exactly how they’re making money on YouTube, July 2020.

[3] H. O. Alwehaibi. The Impact Of Using Youtube In EFL Classroom On Enhancing EFL Students’ Content Learning. Journal of College Teaching & Learning (TLC), 12(2):121–126, Apr. 2015. Number: 2.

[4] M. Arantes, F. Figueiredo, and J. M. Almeida. Understanding video-ad consumption on YouTube: a measurement study on user behavior, popularity, and content properties. In Proceedings of the 8th ACM Conference on Web Science, WebSci ’16, pages 25–34, New York, NY, USA, May 2016. Association for Computing Machinery.

[5] F. Benevenuto, T. Rodrigues, V. Almeida, J. Almeida, and K. Ross. Video interactions in online video social networks. ACM Transactions on Multimedia Computing, Communications, and Applications, 5(4):30:1–30:25, Nov. 2009.

[6] Y. Borghol, S. Ardon, N. Carlsson, D. Eager, and A. Mahanti. The untold story of the clones: content-agnostic factors that impact YouTube video popularity. In Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD ’12, pages 1186–1194, New York, NY, USA, Aug. 2012. Association for Computing Machinery.

[7] Y. Borghol, S. Mitra, S. Ardon, N. Carlsson, D. Eager, and A. Mahanti. Characterizing and modelling popularity of user-generated videos. Performance Evaluation, 68(11):1037–1055, Nov. 2011.

[8] A. Brodersen, S. Scellato, and M. Wattenhofer. YouTube around the world: geographic popularity of videos. In Proceedings of the 21st international conference on World Wide Web, WWW ’12, pages 241–250, Lyon, France, Apr. 2012. Association for Computing Machinery.

[9] A. Bruns. After the ‘APIocalypse’: social media platforms and their fight against critical scholarly research. Information, Communication & Society, 22:1544–1566, Sept. 2019. Publisher: Routledge _eprint: https://doi.org/10.1080/1369118X.2019.1637447.

[10] M. Bärtl. YouTube channels, uploads and views: A statistical analysis of the past 10 years. Convergence, 24(1):16–32, Feb. 2018. Publisher: SAGE Publications Ltd.

[11] M. Cha, H. Kwak, P. Rodriguez, Y.-Y. Ahn, and S. Moon. I tube, you tube, everybody tubes: analyzing the world’s largest user generated content video system. In Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, IMC ’07, pages 1–14, San Diego, California, USA, Oct. 2007. Association for Computing Machinery.

[12] X. Cheng, C. Dale, and J. Liu. Statistics and Social Network of YouTube Videos. In 2008 16th International Workshop on Quality of Service, pages 229–238, June 2008. ISSN: 1548-615X.

[13] A. R. Chow. How a Bollywood Music Label Conquered YouTube. The New York Times, 2018.

[14] A. Clifton and C. Mann. Can YouTube enhance student nurse learning? Nurse Education Today, 31(4):311–313, May 2011.

[15] F. Figueiredo, F. Benevenuto, and J. M. Almeida. The Tube over Time: Characterizing Popularity Growth of YouTube Videos. In Proceedings of the Fourth ACM International Conference on Web Search and Data Mining, WSDM ’11, pages 745–754, New York, NY, USA, 2011. ACM. event-place: Hong Kong, China.

[16] A. Finamore, M. Mellia, M. M. Munafò, R. Torres, and S. G. Rao. YouTube everywhere: impact of device and infrastructure synergies on user experience. In Proceedings of the 2011 ACM SIGCOMM conference on Internet measurement conference, IMC ’11, pages 345–360, New York, NY, USA, Nov. 2011. Association for Computing Machinery.

[17] M. Fisher and A. Taub. How YouTube Radicalized Brazil. The New York Times, 2019.

[18] B. Freeman and S. Chapman. Is “YouTube” telling or selling you something? Tobacco content on the YouTube video-sharing website. Tobacco Control, 16(3):207–210, June 2007.

[19] P. Gill, M. Arlitt, Z. Li, and A. Mahanti. Youtube traffic characterization: a view from the edge. In Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, IMC ’07, pages 15–28, San Diego, California, USA, Oct. 2007. Association for Computing Machinery.
[20] P. Gill, M. Arlitt, Z. Li, and A. Mahanti. Characterizing user sessions on YouTube. In Multimedia Computing and Networking 2008, volume 6818, page 681806. International Society for Optics and Photonics, Jan. 2008.

[21] M. Horta Ribeiro, R. Ottoni, R. West, V. A. F. Almeida, and W. Meira. Auditing Radicalization Pathways on YouTube. In FAT* 2020, 2019.

[22] K. C. Madathil, A. J. Rivera-Rodriguez, J. S. Greenstein, and A. K. Gramopadhye. Healthcare information on YouTube: A systematic review. Health Informatics Journal, 21(3):173–194, Sept. 2015.

[23] I. Orsolic, D. Pevec, M. Suznjevic, and L. Skorin-Kapov. A machine learning approach to classifying YouTube QoE based on encrypted network traffic. Multimedia Tools and Applications, 76(21):22267–22301, Nov. 2017.

[24] R. Ottoni, E. Cunha, G. Magno, P. Bernardina, W. Meira Jr., and V. Almeida. Analyzing Right-wing YouTube Channels: Hate, Violence and Discrimination. In Proceedings of the 10th ACM Conference on Web Science, WebSci ’18, pages 323–332, New York, NY, USA, 2018. ACM. event-place: Amsterdam, Netherlands.

[25] K. Papadamou, A. Papasavva, S. Zannettou, J. Blackburn, N. Kourtellis, I. Leontiadis, G. Stringhini, and M. Sirivianos. Disturbed YouTube for Kids: Characterizing and Detecting Inappropriate Videos Targeting Young Children. arXiv:1901.07046 [cs], Jan. 2019. arXiv: 1901.07046.

[26] Pew Research. Many Turn to YouTube for Children’s Content, News, How-To Lessons, 2018.

[27] B. Rieder, O. Coromina, and A. Matamoros-Fernández. Mapping YouTube. First Monday, 2020.

[28] A. Schwind, C. Midoglu, O. Alay, C. Griwodz, and F. Wamser. Dissecting the performance of YouTube video streaming in mobile networks. International Journal of Network Management, 30(3), May 2020.

[29] N. Shuyo. Language detection library for java. Retrieved Jul, 7:2016, 2010.

[30] S. Siersdorfer, S. Chelaru, W. Nejdl, and J. San Pedro. How useful are your comments? analyzing and predicting youtube comments and comment ratings. In Proceedings of the 19th international conference on World wide web, WWW ’10, pages 891–900, New York, NY, USA, Apr. 2010. Association for Computing Machinery.

[31] Statista. Leading YouTube markets 2016 [https://bit.ly/34NAOV1].

[32] N. Statt. YouTube is a $15 billion-a-year business, Google reveals for the first time, Feb. 2020.

[33] A. Sureka, P. Kumaraguru, A. Goyal, and S. Chhabra. Mining YouTube to Discover Extremist Videos, Users and Hidden Communities. In P.-J. Cheng, M.-Y. Kan, W. Lam, and P. Nakov, editors, Information Retrieval Technology, Lecture Notes in Computer Science, pages 13–24. Springer Berlin Heidelberg, 2010.

[34] S. Wu, M.-A. Rizoiu, and L. Xie. Beyond Views: Measuring and Predicting Engagement in Online Videos. arXiv:1709.02541 [cs], Apr. 2018. arXiv: 1709.02541.

[35] J. Zhou, Y. Li, V. K. Adhikari, and Z.-L. Zhang. Counting YouTube videos via random prefix sampling. In Proceedings of the 2011 ACM SIGCOMM conference on Internet measurement conference, IMC ’11, pages 371–380, New York, NY, USA, Nov. 2011. Association for Computing Machinery.

[36] R. Zhou, S. Khemmarat, and L. Gao. The impact of YouTube recommendation system on video views. In Proceedings of the 10th ACM SIGCOMM conference on Internet measurement, IMC ’10, pages 404–410, New York, NY, USA, Nov. 2010. Association for Computing Machinery.

[37] M. Zink, K. Suh, Y. Gu, and J. Kurose. Characteristics of YouTube network traffic at a campus network - Measurements, models, and implications. Computer Networks: The International Journal of Computer and Telecommunications Networking, 53(4):501–514, Mar. 2009.