An Analysis of the YouNow Live Streaming Platform

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***Abstract*—Video streaming platforms like Twitch.tv or YouNow have attracted the attention of both users and researchers in the last few years. Users increasingly adopt these platforms to share user-generated videos while researchers study their usage patterns to learn how to provide better and new services.**

In this paper, we focus on the YouNow platform and show the results of an analysis of its traffic patterns and other characteristics. To perform this analysis, we have collected YouNow usage patterns for 85994 users over a period of about one month.

Our results show that YouNow's characteristics are in part equal to and in part different from those of other video streaming platforms. Like on YouTube or Twitch.tv, for instance, few YouNow videos attract most of the view requests. On the other side, YouNow sessions are notably shorter than Twitch.tv ones. We believe the observation of these similarities and differences to be crucial to inform the design and implementation of better upcoming video streaming services.

I. Introduction

Online platforms that allow users to share video content have proliferated in the last few years. One of the most popular and mature of such platforms is YouTube[1]. Through YouTube users can easily share their videos and view those previously uploaded by other users. Recently, several other video sharing platforms have emerged, including Twitch.tv[2] and YouNow[3]. Twitch.tv allows users to share videos of gaming sessions or electronic sports (e-sports) competitions, while YouNow is mainly used by children and teenagers to broadcast (and view) self-portrayal videos. Both Twitch.tv and YouNow are online streaming platforms, i.e., viewers can watch videos live while they are generated and uploaded by other users (broadcasters).

Several authors have focused on the analysis of view patterns and other characteristics of video sharing platforms. These analyses inform the definition of guidelines for improving existing platforms and designing new services. For instance, Cha et al. [4], Huang et al. [7] and others have focused on the YouTube platform. More recently, Zhang et al. [16] and Pires et al. [11] have analyzed traffic generated by the Twitch.tv platform.

In this paper, we build upon this line of research and provide an analysis of the view patterns and other relevant characteristics of the YouNow platform. To this end, we collected a data set of YouNow usage patterns of 85994 users for about one month. A preliminary analysis of this data set allowed us to gain a number of interesting insights about relevant characteristics of the YouNow platform. In this paper we show in particular that:

1) About 93% of the live steaming sessions last less than 100 minutes and only 14% of the sessions are longer than one hour. Also, the median length a session is as low as 16 minutes. A typical Twitch.tv session is instead several hours long [11], [16].
2) 80% of the view requests on YouNow are directed towards videos generated by 10% of the broadcasters. Furthermore, 5% of the broadcasters attract no viewers at all. Thus, few *key* broadcasters act as *hubs* that attract most of the viewers while there exists a long tail of weak broadcasters that attract only very few or no viewers. View patterns on the YouTube and Twitch.tv platforms follow a similar behavior [4], [16].
3) An analysis of the type of devices used by YouNow viewers to watch videos reveals that almost 70% of the view requests originate from Apple devices, notwithstanding the fact that Apple's market share worldwide is lower than 20% [6]. This can be explained considering that most users of YouNow are teenagers (among whom Apple products are particularly popular). Furthermore, YouNow has a large user base in the USA, a country that shows one of the highest penetrations of Apple products worldwide.
4) The workload of the platform, regarding the number of viewers and broadcasters is strongly time dependent with up to 17000 viewers during peak times and less than 3000 during low times.
5) Video quality parameters like Frames per Second (FPS) and bitrate, change depending on the type of connection a viewer relies on to broadcast a video. FPS and bitrates are highest when a broadcaster is connected through Wi-Fi and degrade if 4G, 3G or 2G are used instead. Overall, video quality is lower than in other platforms like Twitch.tv.

We describe in the following Section II how we obtained the data set used to derive the insights listed above. We then

[1]www.youtube.com
[2]www.twitch.tv
[3]www.younow.com

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discuss the details of our analysis in Section III and provide an overview of related work in Section IV. Finally, we provide our conclusions and discuss directions for future work in Section V.

II. Data collection

The main source of the videos available on the YouNow platform is the upload of mobile devices such as smartphones and tablets. Thus, YouNow provides dedicated streaming applications for the mobile operating systems with the largest market share such as Android[4] and iOS[5] devices. The main task of those applications is to stream the content to receiving servers which distribute the video over a Content Delivery Network (CDN) to the viewers. Potential viewers get access to the videos trough a webpage or the mobile application.

The YouNow website uses a Representational State Transfer (REST) API providing JavaScript Object Notation (JSON) formatted responses that build the data basis for YouNow's website. An overview of the existing REST resources is listed in Table I. When viewers or broadcasters are visiting the website, requests to those Uniform Resource Locators (URLs) are sent and the returned data is used for rendering the page with the JavaScript based Model View Controller (MVC) framework AngularJS[6].

For video playback, a flash container is generated and embedded in the website that allows video playback using Real Time Messaging Protocol (RTMP). The video streams are encoded using H.264/AVC (high profile) [15] and delivered using the *Wowza Streaming Engine*[7] via the Akamai CDN.

Apart from data relevant for rendering the website and presenting information directly depicted to viewers, internal reporting data is included in the requests' responses, and has been used for analysis in this paper. An overview of all fields available for analysis is given in Table II.

This data contains information regarding the internal reporting system of broadcasting users such as device and connection types of broadcasters, additional user profile information and stream quality indicators.

For the analysis of the system, we periodically (ca. every 5 minutes) requested data from the APIs, in the same way as they would have been used when visiting the website.

Data has been collected for the period between April 09, 2015 and May 15, 2015 and stored in a database for further analysis.

III. Analysis

In the following, we present our findings regarding this emerging type of streaming systems, and analyze the workload over time (Section III-A), the distribution of session durations for broadcasters and viewers (Section III-B), the impact of specific broadcasters on the overall amount of viewers (Section III-C), access patterns of individual most popular broadcasters (Section III-D), which mobile devices are used for broadcasting (Section III-E), and last the quality of the broadcasts in relation to the used network type for the video upload (Section III-F).

Name	Fields
trendingUsers	userId, viewers, likes, tags, broadcastId, username, userlevel, profile, locale, shares, fans, totalFans, lastPosition, position, total
playData	serverTime, channelId, copy, length, shares, quality (bitrate, fps, kfr, percent, desc, high) dynamicPricedGoodies (PROPOSAL_RING, 50_LIKES, FANMAIL, CHATCOOLDOWN), stickersMultiplier, queues, positions, broadcastId, nextRefresh, nextRefreshMobile
info	userId, youtubeStart, giftsValue, lastTopFanAnnounceNew, display_viewers, lastBelowVideoGift, broadcasterBoostLevel, state, media, topFansCount, lastMonitorCheck, dateCreated, coins, mirror, friendsReq, referrals, origCountry, mviewers, username, partner, broadcastId, points, maxTUScore, locale, stateCopy, topFanNew, userlevel, minChatLevel, title, platform, origSettings (bitrate, fps, kf, tcp, videoSize), location, quality, geoLocale, likes, maxConcurrentViewers, brScore, barsEarned, reconnects, stickersMultiplier, shares, totalFans, followersStart, monitorDisconnect, vip, settingsId, dateMonitorDisconnect, lastQuality (bitrate, fps, kfr, percent, desc), facebookId, facebookOption, facebookUrl, twitterHandle, googleHandle, userLevel, description, firstName, lastName, totalFans, youTubeUserName, youTubeChannelId, youTubeTitle, viewers, broadcasterInfo, featuredTime, acceptLanguage, qualitySamples, fbPublish, country, dateStarted, profile, language, broadcastsCount, premiere, maxLikesInBroadcast, twPublish, likePercent, serverTime, length, comments
onlineUsers	users, nextRefresh, totalUsers

TABLE II: Data fields provided by the YouNow REST API.

A. Platform workload

The workload of a broadcasting service, such as Twitch.tv and YouNow, is determined by multiple factors, as it is pointed out in [16]. The number of concurrent broadcasters and viewers is one of such factors. This property plays a key role in characterizing the usage patterns of the YouNow service so as to improve its scalability. To understand the dynamic behaviors of the number of users, including broadcasters and viewers, of the YouNow video service, we count the total number of unique broadcasters for every hour within one week, from May 06 to May 12, 2015. Figure 1 shows the daily access patterns of the number of broadcasters. The format of time is UNIX time stamp.

Figure 1 shows the daily workload patterns regarding the number of broadcasters from all countries. Particularly, it also shows the number of broadcasters from the US and the UK since the majority of broadcasters originate from those countries. This figure shows that broadcasters tend to upload videos mostly in the evening and the number of broadcasters reaches peaks around mid-nights of a Greenwich Mean Time (GMT) day. Broadcasters gradually leave the YouNow video service in the early mornings and join broadcasting sessions

[4]https://play.google.com/store/apps/details?id=younow.live
[5]https://itunes.apple.com/us/app/younow-broadcast-chat-watch/id471347413
[6]https://angularjs.org/
[7]http://www.wowza.com/streaming/live-video-streaming

URL	Name	Description
http://www.younow.com/php/api/younow/trendingUsers/numberOfRecords=10	trendingUsers	Lists broadcasters ranked by their trending status
http://cdn2.younow.com/php/api/broadcast/playData/channelId=⟨channelId⟩	playData	Data for generating the RTMP playback URL given a channelId
http://www.younow.com/php/api/broadcast/info/user=⟨username⟩	info	Detailed user information given a username
http://cdn2.younow.com/php/api/channel/onlineUsers/channelId=⟨channelId⟩	onlineUsers	Data about viewers currently watching a broadcast session

TABLE I: URLs and description of the YouNow REST API used for data collection.

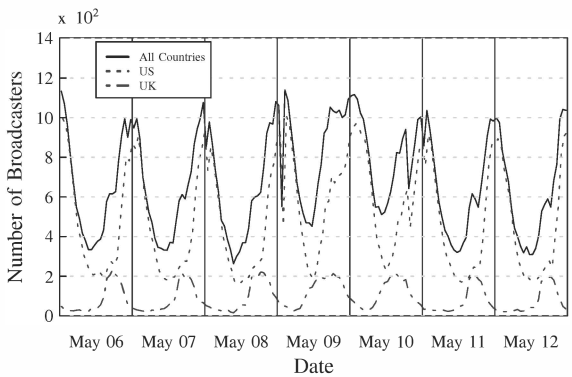

Fig. 1: Plot of the total number of broadcasters on the YouNow platform for the period between May 06 to May 12, 2015.

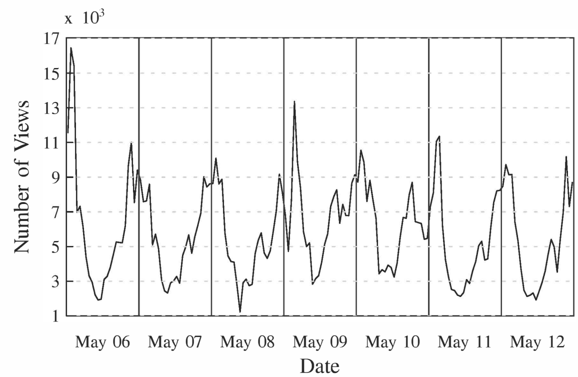

Fig. 2: Plot of the total number of viewers on the YouNow platform for the period between May 06 to May 12, 2015.

in the afternoons. It is interesting to see that the peak number of broadcasters around mid-nights of May 08 and May 09 is slightly higher than other days. The lowest number of broadcasters on May 09 and May 10 are also higher than other days. One possible reason is that May 09 and May 10 are weekend days. Since most of users of YouNow are teenagers, they seem like to have more free time to upload videos on these two days.

Multiple peaks of the number of broadcasters within one day are caused by different timezones. However, the largest peaks can be mainly accounted to the 70% of broadcasters from the US, as depicted in Figure 1. The difference of up to 3 hours between the east coast and west coast of the US has a limited impact since the number of broadcasters from the US is dominantly large. Considering the time differences between timezones used in US and GMT timezones, the number of broadcasters from the US actually reaches the peak in the late afternoon of their local time. Similarly, by examining the access patterns of broadcasters from the UK, there is a peak for video uploads from 3:00 PM to the evening hours of their local time.

Similar to the analysis performed on the number of broadcasters, we also aggregate and plot the number of concurrent online viewers for the same period of time in Figure 2. The number of views is also strongly time-dependent. The number of viewers reaches peaks, which is over $12 * 10^3$ around mid-nights and falls back below $3.5 * 10^3$ around noons. Thus, we can conclude that the viewers of YouNow also tend to watch more videos in the evenings of GMT days.

B. Session duration and online time of broadcasters

A broadcasting session is defined as a pair of create/terminate events of broadcasters and a session duration is the interval between these two events, which is similar to the definition proposed in [9]. The accumulated online time for each broadcaster is calculated by adding session durations initiated by each broadcaster.

Both, session durations and accumulated online time of broadcasters are indicators on the popularity of YouNow. Longer broadcasting sessions and online time indicate high willingness of broadcasters to use YouNow to upload videos.

Like the analysis performed on the number of broadcasters and viewers in Section III-A, this analyses is based on the data collected from May 06 to May 12, 2015.

Figure 3 depicts the distribution of session durations and the online time spent by broadcasters to upload videos. About 93% of the broadcasting sessions last less than 100 minutes and only 14% of the broadcasting sessions last longer than 1 hour. The durations of broadcasting sessions on YouNow are generally shorter than those on other similar broadcasting services, like Twitch.tv, where 30% of the sessions last more than 4 hours. A possible reason for this is that a large share of broadcasting sessions originate from mobile devices and mobile networks (see Section III-E, Section III-F), which imposes limits in terms of data contracts and battery time compared to streaming from stationary clients. Similarly, about 22% of the broadcasters spend more than two hours on uploading videos but there are still around 44% broadcasters spent less than 30 minutes within the evaluated week.

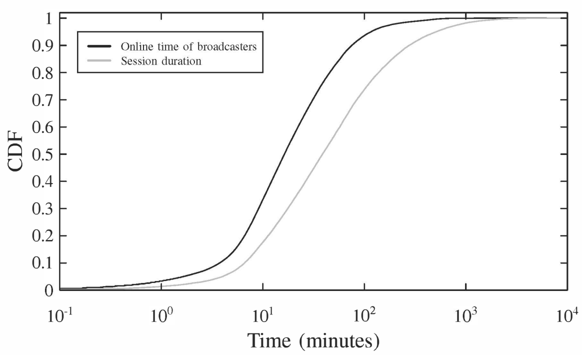

Fig. 3: CDF of session duration and the total online time of broadcasters.

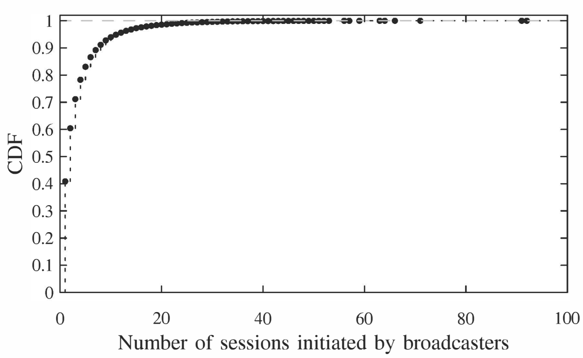

Fig. 4: CDF of the number of broadcasting sessions initiated by users.

Figure 3 in general also shows that the session durations and online time of broadcasters follow a similar distribution. To understand the reason behind it, the distribution of number of sessions initiated by broadcasters within one week is plotted in Figure 4. This figure shows that over 40% broadcasters initiated only 1 broadcasting session and about 10% broadcasters created more than 7 broadcasting sessions within the considered week. This demonstrates that there exists a small group of *highly active* broadcasters that is willing to broadcast several times daily as well as the majority also having limited streaming sessions per week.

C. Broadcaster popularity

The popularity of broadcasters is an important factor for viewers, broadcasters and the YouNow platofrm itself. Viewers may want to know about most popular broadcasters to follow interesting personal shows, while YouNow promotes revenue models and shares profits with popular broadcasters attracting large amount of viewers[8].

Based on the information of viewers in relation to each broadcaster, we have analyzed sessions of 85994 broadcasters to investigate the relationship between the overall number of viewers and the platform's top broadcasts. Here the top 10% of broadcasts are responsible for more than 80% of all views. On the other hand, as depicted in Figure 5, more than 5% percent of broadcasters do not attract any viewers.

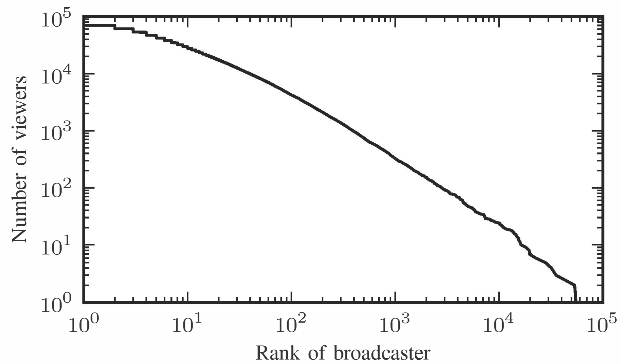

Fig. 5: Relation between share of total views and top ranked viewers.

This shows that most revenue and platform load can indeed be accounted to a small fraction of broadcasters. At the same time, a large share of the bandwidth used for receiving streams is spent without gaining any additional viewers and thus revenue.

D. Access patterns

The information we collected not only allows analysis of session duration as in Section III-B but also derivation of time instances when a broadcaster creates and terminates a broadcasting session.

The access patterns of popular broadcasters are particularly interesting since they attract most of all viewers as shown in Section III-C. Understanding access patterns of popular broadcasters is meaningful for various aspects. It can be simply used to advertise appearance of popular broadcasters to their fans or combined with complex resource allocation policies such as [13]. Particularly, we are investigating if there exist regular access patterns in which each broadcaster tends to upload videos during similar time periods of days or weeks. This hypothesis can be valid for two reasons. First, broadcasters usually upload videos when they are at home or on the way to school. Second, regular patterns of living activities have been proved to exist by research works like [3]. Here, we visually demonstrate the potentials of finding regular access patterns of broadcasters and more complex analyses will be addressed in future works.

Figure 6 plots access patterns of 10 broadcasters who attracted most viewers for the period between May 06 to May 12, 2015. The broadcaster ids have been anonymized and substituted with letters from 'A' to 'J'. They are also sorted and presented in the ascending order of attracted viewers, from up to down. Broadcaster 'A' attracts most viewers among all the broadcasters within this representative time period. Each black rectangular represents a broadcasting session belonging to a broadcaster. Only broadcasting sessions longer than 15 minutes are considered. Figure 6 shows that broadcaster 'F'

[8] http://www.younow.com/partners — accessed on: 27.05.15

regularly start uploading videos around 12:00 AM of GMT zone and broadcasting sessions last around 100 minutes. It also shows that the most popular broadcaster, 'A', usually uploads videos for about 70 minutes within the time frame between 2:30 AM and 5:30 AM of GMT zone. On the contrary, broadcaster 'H' does not exhibit regular access patterns within this representative week although this broadcaster also attracts lots of viewers. We plan to explore the possibility to predict when the popular broadcaster would start a broadcasting session and how long this broadcasting session would be. *Nonlinear time series analysis* used in [14] is a potential method to perform such predictions and we will carry out further analyses on access patterns of more broadcasters.

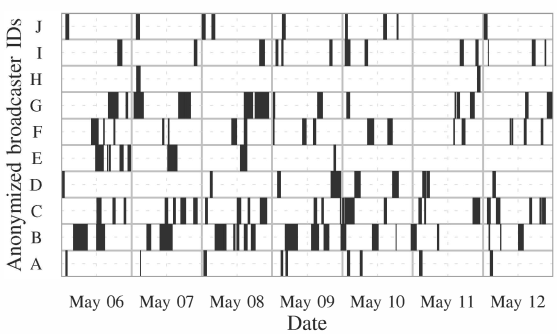

Fig. 6: Access patterns of 10 most popular broadcasters for the period between May 06 to May 12, 2015.

Device type	% of devices
iPhone5	14.38
iPhone6	10.56
iPhone7	9.79
iPad2	9.78
iPod5	7.00
iPhone4	5.91
iPad4	4.01
iPhone3	3.59
iPad3	2.94
iPad5	0.65
LGE LG-D415	0.62
samsung SM-T230NU	0.58
LGE LGMS323	0.56
samsung SCH-I545	0.54
samsung SM-G386T	0.42
Others	28.24

TABLE III: Percentage of reported device type of for each broadcast session as reported by the YouNow API.

Connection type	% of connections
4G	3.0458
3G	1.4307
Wi-Fi	29.8915
Undefined	65.6264
Unknown	0.0021
2G	0.0035

TABLE IV: Percentage of occurrences of broadcast session connection data for different connection types as reported by the YouNow API.

E. Device usage

Given the data about the device types used by broadcasters, we have ranked all devices according to their frequency as presented in Table III.

As shown here, there is a clear dominance of Apple devices for video broadcasting, having a share of almost 70% of all devices used. Following that, there is a large diversity of devices, using the Android system.

According to [6], the global market share of Apple and Android smartphones was 15.4% and 80.7% respectively, in 2014. Therefore, there is clear shift towards the dominance of Apple devices used broadcasting video streams in the YouNow platform.

F. Broadcasting quality

Given the data included in YouNow's internal streaming quality reporting system, we have analyzed the relation between video encoding parameters and the network used for broadcasting streams.

The data classifies different network types, which allow to separate between uploads originating from mobile networks and Wi-Fi. Further, there are two types of unclassifiable data (entries tagged "Unknown" and without any value, which we have labeled Undefined). For sake of completeness, we have included this data in the following figures. However, we did not further analyze them given that we cannot judge on the meaning of those entries.

The data is plotted in Figure 7 for the video bitrate and Figure 8 for the FPS. It shows the median (middle line), the 25th and 75th percentiles (box) as well as the $Q1/Q3 + / - 1.5 * IQR$ (whiskers) for the collected data.

The video bitrate is dependent on the type of network used for the upload. Here, when comparing between 2G and 3G/4G networks, the uploading bitrate for the latter is higher in almost all cases. Wi-Fi connections show a high bitrate variance, with values in the 25th and 75th percentiles overlapping with bitrates of 3G/4G connections.

A possible explanation for this is that the access network for the Wi-Fi connections very diverse, and cause large differences in up- and download bandwidths having the same connection type reported by the system.

Based on the observable ranges of bitrates for different network connection types, there is evidence for the existence of an adaptive broadcast upload, either based on the network type or active bandwidth measurements for determining the bitrate used.

Looking at the FPS shown in Figure 8 of the video stream, there is also significant difference between 2G and other connections. However, for most cases, the FPS does not reach a value higher than 15, independent of the connection type.

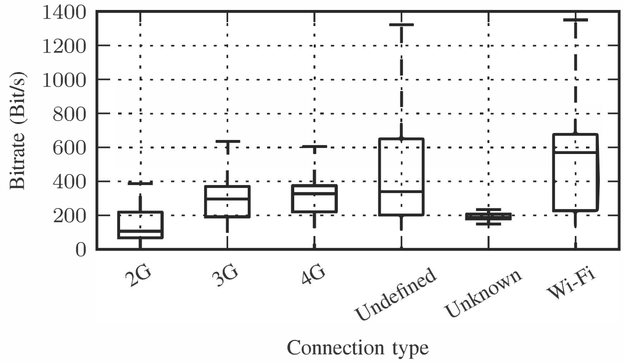

Fig. 7: Boxplots of the uploaded videos' bitrates for different connection types showing the median (middle line), the 25th and 75th percentiles (box) as well as the $Q1/Q3 + / - 1.5 * IQR$ (whiskers).

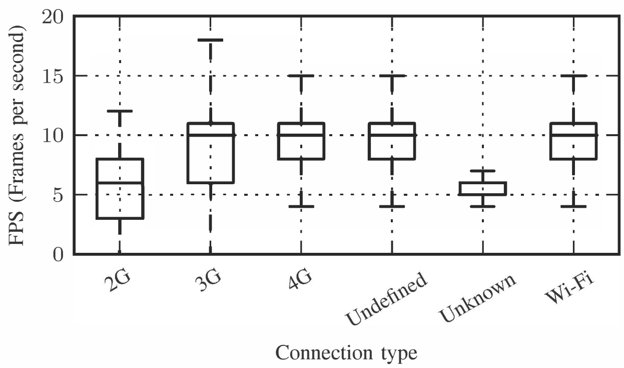

Fig. 8: Boxplots of the uploaded videos' FPS for different connection types showing the median (middle line), the 25th and 75th percentiles (box) as well as the $Q1/Q3 + / - 1.5 * IQR$ (whiskers).

IV. Background and Related Work

The characteristics of videos uploaded to User-generated Video (UGV) platforms such as YouTube have been intensively studied. One early example is the work by Cha et al. [4] whose findings indicate long-tail distribution of user-generated video access. Around 10% of the most popular videos thus account for 90% of the view requests whereas the remaining 90% of the videos are only being viewed not at all or only a few times. Additionally, the authors try to find out what causes the popularity, e.g. the age of a video–showing no significant influence. Already back then the producers of video have been investigated.

The low entry barriers of UGV result in the existence of some heavy producers, who create 1000 and more videos. Still, 90% of all video producers create less than 30 videos. These findings are supported by the research of and supported by Huang et al. [7] who analyzed a nine-month period and gathered 520 million video requests for around 59,000 videos. Their major findings are that video popularity distributions over different days of a week are quite similar.

Similar to our work the bandwidth capabilities of the devices–all stationary laptops or PCs–are investigated. They demonstrate, that back in 2007 in the US only 37% of the users had download rates above 3.5 Mbps. Their assumed upload capacities for such stationary devices is between 384 to 768Kbits. Access to those video is to a large extent mediated by Online Social Networks (OSNs) as shown by Haitao et al. [10].

Ameigeiras et al. [2] also investigated YouTube traffic and the characteristics when the platform is access from a wired network. They characterized the YouTube streaming into an initial burst phase and a throttled transmission phase, managed by the YouTube servers.

In the first phase video is being transmitted at full speed for around 40 seconds. After that in throttled phase the maximum download speed is limited to 1.25 times the video bitrate.

An analysis for mobile devices is given by Ramos et al. [12]. They analyzed mobile terminals based on Google Android and Apple iOS. YouTube networking protocols are thus very diverse, similar to the used buffering approaches to ensure a smooth and continuous video playback. High end devices e.g. use HTTP range requests and establish multiple TCP connections. Even though they mainly use one connection for over 90% of their download this increases fault tolerance. Access to videos is controlled by the video servers of YouTube in a way that they allow in an initial burst phase to download video at full speed, later throttling the video video transmission.

In Finamore's work [5] the network traffic of users accessing YouTube over Wi-Fi is analyzed. In contrast to stationary clients, the mobile video streaming relies on a segment-based approach in which video chunks are aggressively requested using different TCP connections. The TCP connections are used for an initial burst phase in which long ON-OFF transmission patterns have been observed, which are regularly stopping data transfer and thus shaping the download speed [1].

Mobile broadcasting services such as the analyzed YouNow video sharing platform are recently attracting the interest of researchers. For bambuser and qik some successful live video sharing platforms, Juhlin et al. [8] created a classification of video content, showing that most of the shared video streams include test videos. The remaining videos mainly concern casting screens of a laptop or TV.

E.g. Zhang et al. [16] investigated how Twitch.tv, a live streaming platforms for video game broadcasts, video streams are accessed and how video is produced. A specific aspect of the production side is that sources can not only be laptops or PCs but additionally gaming consoles such as XBox or Playstation 4. From a technological view Twitch.tv uses RTMP to stream video from the broadcasters to the servers and then transcodes the video into HTTP Live Streaming (HLS). Twitch is very successful streaming, and has, in peak situations, up to 12,000 parallel video streams. The duration between recording and watching a video is within average 21 seconds quite moderate for HTTP-based delivery of video over a CDN. The popularity of content shared follows a extremely skewed Zipf distribution in which around 0.5% of the broadcast streams account for 70% of the views. Pires et al. [11] explores Twitch.tv and states that those peaks observed generate data traffic of 1 Tbps. In other respect they are supported by the findings of Zhang et al. [16]. In contrast to Twitch.tv, the video platform Vine only includes short running video clips which has been investigated by Zhang et al. [17]. As such video clips do only last several seconds, the data size is very limited. Users are thus unaware of the generated data traffic for their mobile devices and some specific viewing patterns occur–such as passive watching and batch watching of videos.

V. Conclusions and Future Work

In this paper, we provided a preliminary analysis of a data set about usage patterns of the YouNow live streaming platform. We showed that YouNow has peculiar characteristics that are different from those of other video sharing platforms. For instance, YouNow sessions are typically much shorter than Twitch.tv sessions. On the other side, YouNow also shares similar characteristics with other platforms. For instance, the number of viewers per broadcast(er) approximately follows a power law with a long tail, as it also been observed for YouTube. We believe that discovering these similarities and differences among video sharing platforms can help improving existing services and protocols and inform the design of new ones.

As a next step on this line of research we plan to analyze further relevant characteristics of the YouNow platform. In particular, we will investigate in more details the reasons why session durations are significantly lower on YouNow than on Twitch.tv. We believe this might be due to the fact that many YouNow sessions are initiated using mobile devices and while users are mobile while Twitch.tv viewers tend to be more "stationary", e.g., because they watch Twitch.tv videos from home. To make a first step towards verifying this hypothesis, we will explore whether there exist a significant correlation between the duration of a session and the type of device of a user or the connection type. Further, we will analyze the delays between stream up and downloads of videos from different locations and we will investigate whether there exist a correlation between the quality of a streamed video and the number of viewers it can attract. Last but not least, we plan to release our data set to the public and we will thus proceed with the necessary data cleaning and anonymization procedures in the near future.

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