User Behavior and Engagement of a Mobile Video Streaming User from Crowdsourced Measurements

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***Abstract*—Mobile video streaming has gained a lot of popularity in recent year with the introduction of large data plans for mobile phones. While users in non-mobile scenarios have become accustomed to high quality and few stalling events, this is not the case in mobile environments. People are more likely to tolerate stalling since they know high throughput coverage cannot always be guaranteed. Their behavior and their engagement are drastically different when watching videos on mobile devices.**

In this paper, we characterize mobile phone users who use a video streaming application. We present a data set of over 6,000 video views from a crowdsourced video measurement study. We investigate user activity and engagement during video streaming and how such metrics are correlated with each other. This is the first study that goes beyond user engagement and investigates the direct behavior of mobile video users outside the lab which is an important step towards mobile QoE management.

I. Introduction

Video streaming has become the application that consumes the most traffic in the Internet. Video traffic is predicted to make out 78% of the world's mobile data traffic in 2021 [1]. With more people watching videos on mobile devices, a different user behavior should be considers. User engagement is important for ad revenue and customer binding. User interactions are important to investigate the user engagement and user behavior in specific context.

The user engagement describes the time or percentage of the video viewed, i.e. the time between starting to play the video and reaching the end of the video or abandoning it subtracted by pauses or stalls. In [2], a large-scale study of the user engagement of 1.5 million unique users is conducted over a seven month period. They focus on user arrival rates and request patterns and investigate the impact of network and application layer QoS on user engagement. In [3] mobile user engagement is investigated. However the authors do not analyze direct interactions between the user and the video. The authors of [4] investigate the impact of different application layer QoS metrics on user engagement for different types of content. They use a data set with over 1 million users. Based on their results, it is shown that there exists a strong correlation between QoE and user engagement. A stalling ratio-based model for user engagement is presented in [5]. Other metrics that are used to indicate user engagement include the number of comments, the number of votes or likes and the like-dislike ratio. These metrics are usually applied on a video level or on a content provider level [6]. Video content related reasons for declining user engagement and abandonment are described in [7] at the example of a lecture video. Other reasons for abandonment have been studied in a field study in [8] using the browser plugin YouSlow which is described in [**?**].

This paper presents a first attempt to investigating the direct behavior of YouTube users who view videos in a natural setting on mobile devices. Our main research questions are: *Which user actions are correlated? How frequently do users interact with the video player to impact the video playout? How many videos do users watch in a row?* We conducted a four-year long user study with the mobile phone application YoMoApp. It is similar to the YouTube App and was used by 451 devices during the study. After starting our App, the user explicitly agrees to share information with us which helps us evaluate QoE and user related performance metrics. Through the YoMoApp we receive logs from every watched video about every event that occurs while watching the video. These events include stalling, pausing, seeking, quality changes, device rotations, etc. In this paper, we evaluate any data that is related to the user behavior and user actions in detail and present the results.

The remainder of this paper is structured as follows. In Section II we present the methodology of the user study and the data set. Section III discusses results of the study and the model we can deduct from it. Concluding remarks and outlook are given in Section IV.

II. Data Set and Crowdsourced Measurement

The tool YoMoApp [9] is an application for YouTube crowdsourced QoE measurements publicly available on the Google Play Store. It replicates the native YouTube client, giving it the same functionality as the original app. Personal recommendations and favorites are displayed and you can play your previously tagged videos. The goal is to provide a measurement methodology to monitor application-related and user based key performance indicators (KPIs) during a YouTube session. Monitored KPIs were chosen to be highly correlated with the actual QoE of the mobile user. Furthermore, we monitor user interaction such as activating the full screen or changing the playback quality. The app also collects data about the device and the user context, including KPIs such as screen size and orientation, user location, and mobility, and ISP.

The data set we survey consists of more than 6,000 YouTube video views collected by over 70 different mobile operators worldwide and by 451 different users from 2014 to 2018. No user was rewarded for using or downloading the app. The YomoApp allows users to easily check how good his network performs for YouTube streaming which is an incentive to use it over the native YouTube App. We ensure that all users in this data set are natural users by investigating unusual behavior patterns. For example, from July to November 2018, 32 users from Vietnam watched a movie from the *Doraemon* series a total of 1423 times using the YoMoApp. The geographical coordinates of the Doraemon watchers point to an office building of VNPT Technology, the research subsidiary of VNPT which is a Vietnamese telecommunications company. Since they have fixed play intervals with 5, 10, 15, 30, 60 min and many repetitions, this indicates that they were using the YoMoApp to do research and they used the Doraemon video for testing. Since we focus on monitoring normal user behavior, we exclude it from the results of this study, except for Figure 2.

III. Characterization of User Behavior

In this section, we evaluate the data set with focus on user behavior over single videos, multiple videos, and reasons for the behavior. We start by looking at correlations between important measures to point us into the right direction. We then investigate the occurrence of stalls and the active behavior of users, e.g., how often they pause videos. Lastly, we analyze the user engagement and the abandonment behavior of users.

First, we investigate correlations between important measures in Table I. Surprisingly, user engagement only has a small negative correlation of -0.08 with stalling ratio. A stronger correlation was presented in [5] and [10] where it is shown that user engagement can be directly mapped to stalling ratio in non-mobile scenarios. The fact that stalling does not cause abandonment in mobile scenarios indicates that the Quality of Experience has a lower impact on the user engagement in mobile scenarios. This is emphasized by the small positive correlation between user engagement and the number of quality changes. In [10] a negative correlation between user engagement and positive and negative switches was shown for non-mobile scenarios. Furthermore, we see that the number of seeks has a negative correlation with the user engagement. This makes sense since we can imagine impatient users to fast forward more frequently as well as abandon videos earlier. The stalling ratio correlates with stalling duration and with number of stalls which is unsurprising since it is a function of it. The number of stalls correlates with number of pauses, seeks, and slightly with quality changes. That makes sense, since stalling occurs when the user skips to a part of the video that is not yet buffered. Furthermore, users that experience stalling like to pause the video or manually decrease quality to load a large section of the video to prevent further stalling events. Mode switches and screen orientation changes are correlated since orientation changes often trigger full screen mode. Usually, a video will go into full screen mode, if the device is rotated. However, on some devices an orientation change does not lead to a mode change, e.g., when the respective option is deactivated by the user. Inversely, when users manually go into full screen mode they usually want to rotate their device to view the video properly. Therefore, both curves are very close together and are strongly correlated (coefficient of correlation of 0.62). The number of pauses is correlated with the number of seeks since seeking always pauses the video.

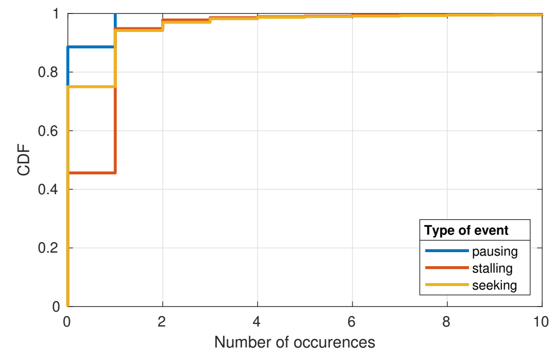

Figure 1. Number of pauses, seeks and stalls that occur during a video.

A. User Interactions

In Figure 1 we see three kinds of events that interrupt the flow of the video: pausing, stalling and seeking. Almost 90% of videos were not paused once and only very few videos are paused more than once. Most pauses are shorter than two seconds. However, several users pause their video for a very long time. The longest pause recorded was longer than two days. Since the YoMoApp was not closed during this pause we still consider it as a single video session. More common than pausing is seeking, which occurs in about 75% percent of videos. Since a HTML media element is not always returned after seeking, it is not possible to present the duration of seeking events. Stalling was the most frequent event that interrupted the video playout. However, it is the only event that is triggered involuntarily and has a negative impact on the user experience. Stalling events were also much shorter than pauses, most of the time. Notice that we do not consider initial delay as stalling.

B. User Engagement and Video Abandonment Behavior

The above investigated user actions affect and extend the total amount of time a user spends on a video and how long he/she stays on the video page. The time users spend on a video consists of watching, stalling, initial delay, pausing and seeking. For the user engagement we only consider the time spent watching. In Figure 2 we investigate the relative user engagement as a share of the video length. When a video is not abandoned a time slightly higher 100% is expected. Higher times occur because some people rewind the video to watch certain scenes multiple times. Most YoMoApp users only watch a single video during a session. Only about 1.1% of users watched more than ten videos in a single session.

When a video runs in full screen mode and the user wants to abandon the video, he first needs to leave full screen mode.

coef. of corr.	user eng.	stalling ratio	stalls	mean stall dur.	full screen	screen rotations	pauses	seeking	quality changes
user eng.	-	-0.0828	-0.0199	-0.0113	0.0967	0.1502	0.0121	-0.1018	0.1405
stalling ratio	-0.0828	-	**0.9520**	**0.9782**	-0.0109	-0.0099	**0.2329**	0.0821	0.0976
stalls	-0.0199	**0.9520**	-	**0.9484**	0.0240	0.0292	**0.2679**	0.1303	0.0946
mean stall dur.	-0.0113	**0.9782**	**0.9484**	-	0.0092	0.0173	**0.2315**	0.0742	0.1206
full screen	0.0967	-0.0109	0.0240	0.0092	-	**0.6957**	0.1209	0.0670	-0.0045
screen rotations	0.1502	-0.0099	0.0292	0.0173	**0.6957**	-	0.0775	0.0261	0.0179
pauses	0.0121	**0.2329**	**0.2679**	**0.2315**	0.1209	0.0775	-	**0.2404**	0.0104
seeking	-0.1018	0.0821	0.1303	0.0742	0.0670	0.0261	**0.2404**	-	0.0507
quality changes	0.1405	0.0976	0.0946	0.1206	-0.0045	0.0179	0.0104	0.0507	-

Table I
SPEARMAN COEFFICIENT OF CORRELATION BETWEEN INTERESTING MEASURES.

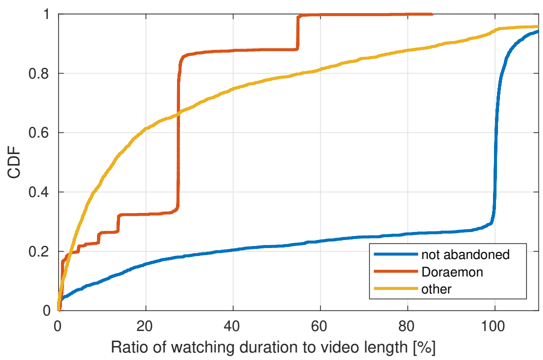

Figure 2. Relative user engagement, i.e., ratio between user engagement and video length.

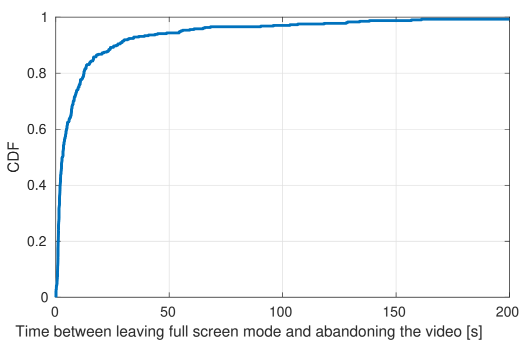

Figure 3. CDF of time that passed between leaving full screen mode and abandoning the current video.

We suspect that this is a primary reason to leave full screen mode. In Figure 3 we therefore determine the time between the last change from full screen mode to normal mode and the point in time where the video is abandoned. Indeed, 50% of users abandon the video within three seconds of leaving full screen mode. However, over 5% of users only abandon the video 50 seconds or later after leaving full screen mode.

IV. CONCLUSION

To optimize adaptive streaming algorithms, it is necessary to know more about the user activity during video streaming. In this paper, we present a data set of mobile user behavior during video streaming that was measured over multiple years using the YoMoApp which offers access to YouTube videos. Our measurement results show that many user actions are correlated. For example, stalling, pausing and seeking often occurs in similar ratios. We found that mobile users are less likely to abandon a video due to stalling than non-mobile users. Particularly interesting is the fact, that we can use "leaving full screen" as a trigger to stop further downloading the current video or start downloading the next video. This might be a cornerstone for future work.

In future work, we want to focus on session level behavior of users and build a model for behavior patterns of bingers and seekers. Furthermore, we want to investigate whether we can use behavioral information for non-linear segment requests in adaptive streaming algorithms.

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REFERENCES

[1] Cisco, "Cisco visual networking index: Forecast and methodology 2016–2021." 2017.

[2] H. Yu, D. Zheng, B. Y. Zhao, and W. Zheng, "Understanding user behavior in large-scale video-on-demand systems," in *ACM SIGOPS Operating Systems Review*, vol. 40, no. 4. ACM, 2006, pp. 333–344.

[3] M. Z. Shafiq, J. Erman, L. Ji, A. X. Liu, J. Pang, and J. Wang, "Understanding the impact of network dynamics on mobile video user engagement," in *ACM SIGMETRICS Performance Evaluation Review*, vol. 42, no. 1. ACM, 2014, pp. 367–379.

[4] F. Dobrian, A. Awan, D. Joseph, A. Ganjam, J. Zhan, V. Sekar, I. Stoica, and H. Zhang, "Understanding the impact of video quality on user engagement," *Communications of the ACM*, vol. 56, no. 3, pp. 91–99, 2013.

[5] C. Moldovan and F. Metzger, "Bridging the gap between QoE and user engagement in http video streaming," in *28th International Teletraffic Congress (ITC 28)*, vol. 1. IEEE, 2016, pp. 103–111.

[6] L. A. Liikkanen and A. Salovaara, "Music on YouTube: user engagement with traditional, user-appropriated and derivative videos," *Computers in Human Behavior*, vol. 50, pp. 108–124, 2015.

[7] A. McGowan, P. Hanna, and N. Anderson, "Teaching programming: Understanding lecture capture YouTube analytics," in *Proceedings of the 2016 ACM Conference on Innovation and Technology in Computer Science Education*. ACM, 2016, pp. 35–40.

[8] H. Nam, H. Schulzrinne, and K. Kim, "Youslow: What influences user abandonment behavior for internet video?" *Columbia University, Tech. Rep.*, 2016.

[9] F. Wamser, M. Seufert, P. Casas, R. Irmer, P. Tran-Gia, and R. Schatz, "Yomoapp: A tool for analyzing QoE of YouTube http adaptive streaming in mobile networks," in *2015 European Conference on Networks and Communications (EuCNC)*. IEEE, 2015.

[10] M. Plakia, E. Tzamousis, T. Asvestopoulou, G. Pantermakis, N. Filippakis, H. Schulzrinne, Y. Kane-Esrig, and M. Papadopouli, "Should i stay or should i go: Analysis of the impact of application QoS on user engagement in YouTube," *arXiv preprint arXiv:1901.01603*, 2019.