QoE Matters More Than QoS: Why People Stop Watching Cat Videos

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Abstract—With the proliferation of online video, measuring quality of experience (QoE) has become a pivotal aspect for the analysis of today’s over-the-top (OTT) video streaming. For monitoring video QoE, we introduce YouSlow that can detect various playback events (e.g., start-up latency, rebufferings and bitrate changes) from video players while a video is being played. Using YouSlow, we have collected more than 400,000 YouTube views from more than 100 countries.

We investigate the impact of the above playback events on video abandonment: rebufferings can cause abandonment rate six times higher than a start-up latency which is mostly caused by pre-roll ads in YouTube. In addition, our analysis shows that a single rebuffering event can cause abandonment rate three times higher compared to a single bitrate change. Further, we present that even increasing a bitrate can raise abandonment rate more than four times higher than a case with no bitrate changes.

Index Terms—HTTP Video Streaming; Adaptive Bitrate (ABR) Streaming; Video Quality of Experience (QoE)

I. INTRODUCTION

Today’s popular video streaming services (e.g., Netflix, Hulu and YouTube) stream video contents to viewers over HTTP or HTTPS. To provide smooth streaming, they use adaptive bitrate (ABR) streaming technologies such as Apple’s HTTP Live Streaming (HLS) [1], Microsoft’s Smooth Streaming (SS), Adobe’s HTTP Dynamic Streaming and Dynamic Adaptive Streaming over HTTP (DASH) [2]. In ABR streaming, a video player dynamically adjusts video bitrates based on estimated network conditions, buffer occupancy and hardware specifications of viewers’ devices (e.g., smartphones vs. desktops). Therefore, user-perceived video quality can vary depending on how appropriately the player selects the best available bitrate during a download. As an example, a viewer may experience frequent rebufferings (i.e., a video is paused and played repeatedly) when the player requests a higher bitrate than what is actually available in the network. It is also possible for the viewer to be stuck with a low bitrate during the entire playback if the network capacity is underestimated by the player. Hence, from over-the-top (OTT) video service provider’s viewpoint, improving ABR heuristics is a key factor to enhancing video QoE.

To improve ABR streaming, it is important to analyze the impact of changes of ABR heuristics on video QoE. While traditional quality of service (QoS) based metrics (e.g., measuring TCP throughput, video packet delay and jitter) can be used to pinpoint network impairments, the metrics do not accurately reflect the viewer’s watching experience. Thus, we believe that the QoE monitoring system should focus on application-layer events instead of transport-layer events. To achieve this, we suggest monitoring live playback events directly from video players rather than the network middleboxes (e.g., routers). As a proof of concept, we have developed YouSlow (“YouTube Too Slow!?”), a new QoE monitoring system for OTT streaming services. This lightweight web browser plug-in can monitor various playback events such as start-up latency, rebufferings and bitrate changes directly from ABR players while viewers watch videos in YouTube web site. So far, YouSlow has collected over 400,000 YouTube views from more than 900 viewers located in more than 100 countries.

In this paper, we evaluate various QoE metrics by analyzing video abandonment rates in YouTube. An abandonment is a case where a viewer closes video in the middle of a playback due to lack of interest or the annoyance caused by various playback events such as long start-up latency, frequent rebufferings and bitrate changes. Our key findings and contributions can be addressed in three folds below:

• Development of an analysis tool for video QoE: YouSlow is designed to detect various playback events while a video is being played. Compared to prior approaches using survey-based metrics, it is more time- and cost-saving for video researchers to collect a large number of data samples. In addition, our QoE monitoring system can support viewers to track their viewing experiences (e.g., statistics of average played bitrates and rebufferings) in real time.

• Development and evaluation of QoE metrics: We show that tracking rebuffering ratio and bitrate changes over playback time is useful to quantify abandonment rates for short videos. We suggest an ABR player to use the metrics to improve user engagement, when switching bitrates and inserting ads in the middle of a playback.

• An analysis of YouTube: Our measurements show that rebufferings increase abandonment rate six times higher than a start-up latency which is mostly caused by pre-roll ads in YouTube. Most interestingly, our analysis shows that even increasing a bitrate during playback can annoy viewers; when the bitrate changes, they abandon videos more than four times as much. Further, we show that a single rebuffering event can cause abandonment rate three times higher than a single bitrate change.

The remainder of this paper is organized as follows. In Section II, we focus on understanding the principle of ABR
streaming, and address the challenges of estimating video QoE using network QoS metrics. Section III describes the overview of YouSlow and its implementation. Then, we present our analysis of YouTube in Section IV. Our QoE analysis report is described in Section V. Finally, we look at the related work and summarize our conclusions in Section VI and VII, respectively.

II. BACKGROUND

We briefly describe today’s HTTP based video streaming technologies. Further, we address the challenges of estimating video QoE using QoS based metrics.

A. Progressive download vs. ABR streaming

Today’s video streaming typically uses the two popular HTTP-based streaming technologies: progressive download and ABR streaming. Before ABR streaming gained popularity, progressive download was used most widely. In progressive download, a video server streams a single video file when a video is requested. The disadvantage of using this technology is that the viewers had to watch the same quality of video regardless of their local network conditions or hardware specifications of their devices. ABR streaming technology was introduced to resolve this problem. In ABR streaming, a video server contains multiple bitrates and a player selects the best available bitrate regarding various factors such as real-time available network bandwidth, remaining playout buffer occupancy, screen resolution and video rendering capability of the viewer’s device. Each bitrate is segmented into a series of small fragments and the duration of fragment varies between two to ten seconds.

As shown in Figure 1, an ABR player operates based on three components: a playout buffer, a bandwidth estimator and ABR heuristics. Using a bandwidth estimator, the player monitors available throughput during a download. Based on the download speed and the remaining playout buffer level, ABR heuristics in the player are used to select the best available bitrate while the video is being played. In addition, ABR heuristics take into account hardware specifications of viewers’ devices for the bitrate selection algorithm. For example, the player selects high definition (HD) bitrates on desktop browsers while it generally plays standard definition (SD) bitrates on smartphones due to small screen size and low graphics processing unit (GPU) performance.

OTT service providers typically use different fragment duration, playout buffer size and ABR heuristics. Thus, even if the same ABR technology is used by several OTT service providers, the performance of ABR streaming can vary.

B. Challenges of analyzing video QoE using QoS metrics

Several researchers [3]–[5] have used QoS based metrics (e.g., monitoring throughput, goodput, packet delay and jitter from network middle-boxes between viewers’ devices and video servers) to estimate video QoE. However, while the metrics can provide a certain level of accuracy, there are still challenges to precisely estimating QoE for buffered video streaming. As an example, low TCP throughput does not always interrupt viewer’s watching experience. For instance, let’s suppose that an ABR player has downloaded enough data in the playout buffer. In this case, even if the network has low TCP throughput, the player can still provide smooth streaming until it consumes every data stored in the buffer. Moreover, it is possible for the player to experience low frame rate when there is a significant number of packet loss during a download, which can degrade QoE of viewers. To avoid this, an ABR player is designed to flush the playout buffer and try to download the entire fragments again. The QoS based metrics are unable to detect the above events since they cannot accurately track the playout buffer level from the network middle-boxes.

III. IMPLEMENTATION

Unlike prior QoS based metrics, YouSlow can monitor various playback events directly from an ABR player for an analysis of video QoE. Currently, YouSlow only supports YouTube, but can be also applied to other OTT video streaming services such as Netflix and Hulu.

Figure 2 shows the architecture of the Chrome plug-in for YouTube analysis. We distribute the extension via Chrome web store1 and YouSlow web site2. YouSlow runs in the background of the Chrome browser, and injects our QoE monitoring scripts into the web page whenever a viewer watches a video in YouTube web site (e.g., www.youtube.com). The core scripts contain YouTube player’s IFrame and JavaScript APIs [6] to access and monitor playback events of HTML5 and Flash video players. When a viewer ends a video session, the extension automatically reports the measurements to our monitoring server2. The collected data is analyzed and then marked on Google maps. We note that the extension does not collect any information regarding the viewer’s YouTube account or video titles.

Through our monitoring system2, viewers can monitor various feedbacks on their YouTube watching experiences, such as how often they experience rebufferings and what video bitrates they typically watch in YouTube. Using this information, they may compare the performance of their own ISPs with other local ISPs. Additionally, YouSlow outputs can be useful to the video service providers when improving their ABR streaming services. For example, they can monitor and compare the rebuffering statistics every time there is a change in their ABR heuristics.

1Chrome web store - http://goo.gl/AIOED3
2YouSlow - https://dyswis.cs.columbia.edu/youslow/
YouSlow can measure the following factors during video playback:

- **Start-up latency:** It measures a start-up delay, which is from the instant a play button is clicked to when the player actually starts to play the main video.
- **Rebuffering:** It monitors the duration of rebuffering and how often it appears during playback.
- **Bitrate changes:** It measures how much an ABR player increases or decreases bitrate, every time it switches bitrate during playback.
- **Video loaded fraction:** It monitors the percentage of the video that the player shows as buffered. We calculate the fraction by dividing the total amount of downloaded video data by the full size of the video. For example, if the player downloads 10 MB from a 100 MB video, the fraction will be 0.1.
- **Location:** An IP geo-location database\(^3\) is used to pinpoint the approximate location (e.g., city, state, country) of the playback event, and find the hostnames of local ISPs that the viewers are connected to.

### IV. YouTube Measurements

In this section, we analyze 409,511 YouTube views collected between April 2014 and July 2015, from more than 900 viewers in 102 countries. We note that the dataset only includes the video sessions where the viewers watched videos through YouTube web site using the Chrome browser on desktops or laptops. The Chrome extension does not operate on mobile platform such as iOS and Android. Table Ia shows the top ten countries along with the total number of reported views. We also compare and analyze the measurements regarding U.S. ISPs (Table Ib).

**Start-up latency:** We measure the elapsed time from when a play button is clicked to when the main video starts. There are two factors that contribute to start-up latency: playout buffer and pre-roll advertisements (ads). First, an ABR player has to wait until a certain amount of video data is stored in the playout buffer. Secondly, an ABR player does not play the selected video until viewers watch video ads. According to YouTube’s advertising policies [7], there are two types of video ads in YouTube: **skippable** and **non-skippable**. Skippable video ads allow viewers to skip the ads after 5 seconds while non-skippable video ads must be watched to view the main video. Both ads can appear before, during or after the main video. After the ads are viewed at least one time, they may not appear for a certain period of time. We also note that the viewers who use an ad-block extension [8] may not experience YouTube ads during the entire playback. Our tool can distinguish whether the start-up latency is caused by the pre-roll ads or the lack of data stored in the buffer by comparing HTTP URLs using Chrome webRequest API [9].

We observe, the player uses different URL parameters for downloading the video ads and the main video. Through the measurements, we find that in most cases (>99%) the pre-roll ads are the cause of start-up latency for YouTube videos and its average duration is 6.4 seconds per video session.

**Video watching duration:** We measure how long a viewer stays in each video session. The watching duration also includes rebuffering duration and start-up latency. Based on the experimental results in Figure 3a, we observe that the viewers watched YouTube videos for 5:01 minutes on average per video session.

**Video loaded fraction:** We measure video engagement by monitoring the video loaded fraction described in Section III. According to Figure 3b, more than 40% of viewers closed YouTube videos in the middle of the playback. They may have lost their interest in the videos or suffered from unexpected playback events such as rebufferings and bitrate changes. We will describe QoE assessments in more detail in Section V.

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\(^3\)Maxmind GeoIP database - http://dev.maxmind.com/
Communications, Comcast and AT&T’s HFC from Time Warner Cable, Charter Communications, Cox from Verizon’s FiOS.

Details, we compare the distributions depending on different
of played bitrates via different ISPs in United States. For more
did not switch bitrate throughout the entire playback. We
typically observe low number of bitrate switches when the
network condition is reliable to play the selected bitrates
switches in the dataset. 80% of video sessions in YouTube
have less than three bitrate switches during playback.

Bitrate switches: We observe that most video sessions
(> 98%) have less than three bitrate switches during playback.

Figure 5 shows the probability mass function (PMF) of bitrate
switches in the dataset. 80% of video sessions in YouTube
switches affect viewing interruption?

Played bitrates: According to YouTube’s encoding policies
[10], YouTube streams eight different bitrates: highres, hd1440, hd1080, hd720, large, medium, small and tiny. We describe each bitrate setting in Table IIa, and measured the distribution of played bitrates in Table IIb. These measurements indicate that most viewers on desktops or laptops watched YouTube videos with large (36.1%) or medium (26.8%) bitrates. We also observed a few number of hd1440 and highres, but the probability (< 0.1%) is much smaller.

In Figure 4a, we compare the distributions of played bitrates among countries. For example, the viewers in United States and South Korea experienced higher bitrates in comparison to
the ones in India and Egypt. Figure 4b shows the distributions of played bitrates via different ISPs in United States. For more
details, we compare the distributions depending on different
types of Internet connections such as fiber-optic cables, hy-
brid fiber-coaxial (HFC) and digital subscriber line (DSL).

We collected 7,074 samples in total for fiber-optic cables from Verizon’s FiOS Internet service, and 6,618 samples for HFC from Time Warner Cable, Charter Communications, Cox Communications, Comcast and AT&T’s Lightspeed. For DSL,

we obtained 2,384 samples from Verizon (non-FiOS), AT&T (non-Lightspeed) and Qwest Communications. YouSlow can
distinguish this by comparing the hostnames of the Internet
service providers of the viewers using the IP geo-location
database1. For example, Verizon uses certain hostnames (e.g.,
x.x.fios.verizon.net) for the FiOS users. Through the measurements,
we observe that the viewers using fiber optics watched
more HD bitrates (36.8%) than the ones using HFC (25.3%)
or DSL (14.4%).

Rebufferings: In the dataset, we observe that more than 99% of video sessions have less than four rebufferings during entire playback. Figure 6 shows the PMF graphs of total number and total duration of rebufferings per video session. In addition, the figures represent the best fitting distributions. For the number of rebufferings, we find the two distributions which fit the
data: Binomial (number of trials = 3 and probability = 0.368)
and Poisson (lambda = 1.104). Geometric (probability = 0.243)
is the best fitting distribution for the total rebuffering duration.

Through these measurements, we find that in most cases, the
viewers experienced a few number of rebufferings and the total
duration of rebufferings was relatively short.

V. VIDEO QOE ANALYSIS

In this section, we describe our analysis of video QoE based
on the YouTube measurements in Section IV. We are trying to
answer the following questions:

• How does start-up latency, rebufferings and bitrate

changes affect viewing interruption?
• What metrics can we use to analyze the impact of the above playback events on video QoE?

A. Analysis methodology and metrics

Unlike Netflix and Hulu that stream long videos (e.g., movies and TV shows), YouTube typically provides short video clips (e.g., music videos and sports highlights). Most viewers access YouTube videos while surfing the Internet and the videos are easily abandoned if the viewers lose interest during playback. We monitor such video abandonment for an analysis of video QoE. Instead of monitoring video packets [11], YouSlow can obtain this data more accurately by monitoring playback status (e.g., play, pause and stop) directly from the video players.

We want to point out how we distinguished the videos that were abandoned due to poor viewing experiences (such as frequent bitrate changes and rebufferings) from the videos that were abandoned due to lack of interest by the viewers or other interruptions unrelated to the viewing experience. The abandonment case lead by rebufferings is quite straightforward. YouSlow can distinguish if a video is paused by the viewer or a rebuffering event. Therefore, when a video is closed while it is paused due to rebufferings, we consider the case as an abandonment. For the case of bitrate changes, it is more complicated. For example, it is difficult to tell if viewers are closing the videos due to bitrate switches or simply because they lost interest (along with bitrate change experience). To minimize the case, we assume abandonment when a viewer closes the video within five seconds followed by the bitrate changes, after the viewer watches at least half of the full content of the video. But since above requirements work only with longer videos, the videos that are shorter than 30 seconds are excluded from the dataset for the analysis. Overall, we believe that it is safe to calculate the abandonment rate with above methods by dividing the number of video sessions with abandonments (due to above viewing interruptions) by the number of video sessions with or without abandonments.

Compared to mean opinion score (MOS) based metrics that can have multiple numbers to reflect service quality (e.g., a numerical value between 1 and 5), YouSlow returns only two values for each video session: 0 (non-abandoned) or 1 (abandoned). There may be exceptional cases where a viewer watches the video to the end even if the viewer had a bad watching experience throughout the entire playback. However, with a large number of samples, we believe that monitoring abandonment rates gives us more practical and reliable outputs to analyze viewing interruptions.

B. QoE analysis report

1) Rebuffering: Most recent studies on video QoE [3], [12]–[15] agree on the fact that rebufferings should be avoided at all times to enhance video QoE. In addition, they show that QoE of viewers can vary depending on a rebuffering pattern (i.e., how many or how often rebufferings appear during playback). In this paper, we try to understand how viewers react to such different rebuffering patterns in YouTube, along with abandonment rates. As a baseline analysis, we extract the video sessions from the dataset where the total number of rebufferings is three, and plot the abandonments based on the rebuffering intervals. The interval represents the elapsed time among consecutive rebufferings as shown in Figure 7.

Figure 8 shows our experimental results. Through the measurements, we first find that there are more abandonments when the rebuffering intervals are short. We frequently observe such short rebuffering intervals when an ABR player requests a higher bitrate than what a network can handle. In this case, the video play has to be paused until the player stores a certain amount of data in the buffer, which can cause a series of short-term rebufferings. Furthermore, we observe that an abandonment pattern varies depending on rebuffering intervals. For instance, let’s suppose that we have a certain range of first rebuffering interval between 0 and 10 seconds in Figure 8. Depending on the second interval, we clearly see that the distribution of abandonments varies. The question is, how do we normalize the impact of rebuffering intervals and correlate the results with QoE assessments (e.g., MOS)? If we
However, we note that the rebuffering ratio does not take into account more number of rebufferings or additional factors such as rebuffering duration and total playback length. QoE modeling will be much more complicated. To avoid such complexity, we consider a simpler metric below and analyze how the metric predicts the abandonment rate.

Rebuffering ratio: We analyze the impact of rebufferings on abandonment rates using rebuffering ratio. The ratio is defined as the fraction of time when a viewer experiences rebufferings while watching a video. As an example, let’s suppose that rebufferings occur for ten seconds while a viewer watches a 90 second video. In this case, the rebuffering ratio will be 10/(10+90) = 0.1.

Using the above methodology, we calculate the abandonment rate from the dataset. Figure 9 shows our experimental results. As a baseline analysis, we observe 1.2% of abandonment rate for the video sessions with no rebufferings (ratio = 0). We note that the abscissa indicates a range of rebuffering ratio (x - y represents x < ratio ≤ y) and the value in the parenthesis shows the number of samples. For example, we count the number of video sessions with a certain rebuffering ratio (e.g., 0.06 < ratio ≤ 0.08). There are total of 1,983 samples. Among them, the number of video sessions where the viewers closed the videos during the rebufferings is 83. Therefore, the abandonment rate is 4.2% (∼ 83/1,983). The results tell us that more viewers abandoned the videos as the rebuffering ratio increased.

However, we note that the rebuffering ratio does not take account of the number of rebufferings. As shown in Figure 10, for instance, it is possible that the number of rebufferings can vary although the total rebuffering duration is the same. This can affect video QoE differently. To prove it, we compare the impact of a single rebuffering event and multiple rebufferings by comparing the abandonment rates along with rebuffering ratio. Figure 11 shows our experimental results. We clearly see that an abandonment rate rises in both cases as the rebuffering ratio increases, but multiple rebufferings cause higher abandonment rates over a single rebuffering event. Especially when the buffering ratio is larger than 0.5, the abandonment rate for multiple rebufferings is about three times higher than the one for a single rebuffering event.

According to Figure 6a in Section IV, most video sessions in the dataset have a small number of rebufferings (between 1 and 3). We investigate the abandonment rates depending on these numbers. Figure 12 shows our experimental results. Considering the single rebuffering results in Figure 6a, we note that the right side of the graph (e.g., ratio > 0.3) represents the results of the videos with short watching duration and the left side is for the results of videos with a relatively long watching period. For example, the former case is that the viewer closed the video during 10 seconds of rebufferings after watching 10 seconds of the video (ratio = 0.5), and the latter case is that the viewer closed during the same length of rebufferings but after watching 90 seconds (ratio = 0.1). This confirms the results that the abandonment rate varies depending not only on rebuffering duration but also video playback length. We observe that a single rebuffering event shows relatively lower abandonment rate compared to two or three rebufferings, even if they have the same rebuffering ratio.
all the bitrate switching events, such as the number of bitrate changes, its amplitude (i.e., how much bitrate increases or decreases) and the duration of each bitrate. Below, we try to find a simple metric that can properly reflect and quantify the impact of bitrate changes on abandonment rates in YouTube.

**Bitrate change ratio**: To find the impact of bitrate switching on abandonment rates, we take into account absolute values of bitrate changes over playback time using Equation 1.

$$\text{Ratio} = \frac{\sum_{i=1}^{\text{Num. of BR changes}} |BR_i - BR_{i-1}|}{\text{Total playback duration (second)}}$$

The $BR_i$ and $BR_{i-1}$ denote the newly selected bitrate and the previous bitrate (in kbps), respectively. Using the above equation, we calculate the abandonment rates. To remove the influences of other factors (e.g., rebufferings and ads), we first collect the video sessions with bitrate changes only. To avoid the case where a video is closed due to lack of interest, we only considered the ones that were watched at least half of the full length and closed within five seconds after the bitrate changes in the middle of a playback. As a baseline analysis, we observe 1.1% of abandonment rate for the video sessions with no bitrate changes (ratio = 0).

The absolute ratio line in Figure 13 shows our experimental results. It tells us that more viewers abandoned videos when more number of bitrate changes (increase or decrease) appeared during playback. For instance, when the bitrate change ratio is between 30 and 40, the abandonment rate becomes more than four times higher than the case with few bitrate changes (0 < ratio ≤ 5). This result leads to the following question: does switching to a higher bitrate during playback also increase abandonment rate? To figure this out, we analyze the video sessions where the player always switched bitrate to higher ones (e.g., $BR_i > BR_{i-1}$). During the entire playback, in the other words, it never decreased the bitrates. We also calculate the abandonment rates for the video sessions where the player never increased the bitrates during playback. Through the measurements in Figure 13, we clearly see that when decreasing bitrates, more viewers abandoned the videos. Interestingly, we also observe that more viewers abandoned the videos, even when the players tried to increase the bitrates. For instance, when the bitrate change ratio is between 30 and 40, the abandonment rate becomes 4.9%, which is more than four times higher than the case with no bitrate change (ratio = 1.1%).

### Start-up latency vs. rebuffering:

We calculate abandonment rate for a start-up latency (i.e., a video is closed during the initial delay before the main video starts), and compare it with the rebuffering case. But, the same methodology used for the calculation of rebuffering ratio cannot be used for a start-up latency. The main reason is that during a start-up latency, the ratio is always going to be 1 since the main video never played (e.g., $\frac{\text{initial delay}}{\text{buffering time (s) + latency}}$). The ratio will become lower than 1 after the main video starts. In this case, the high ratio means that the video is closed soon after the start-up latency ended. This abandonment typically occurs when the video is not what the viewer intended to watch.

Alternatively, we approach with the following method: We first categorize the dataset into two groups. The first group contains the video sessions where there is only a start-up latency (mostly caused by the pre-roll ads according to Section IV) and no rebuffering throughout the rest of the playback. In the second group, the video sessions experience a very short start-up latency (< 1 second) that viewers may not notice and only a single rebuffering in the middle of the playback. We take into account only the video sessions with a single rebuffering event so as to avoid the influences caused via multiple rebufferings.

In both groups, we count the number of video sessions abandoned by the viewers during either the start-up latency or the rebuffering, and the numbers are divided by the total number of video sessions in each group. As a result, we observe an abandonment rate of 0.6% ($\approx 269/44,829$) for a start-up latency and 3.9% ($\approx 807/20,690$) for a single rebuffering event.

To strengthen the results, it would be better to compare the abandonment rates between the start-up latency caused by initial buffering and the pre-roll ads. Due to lack of samples for the buffering case, however, we leave this as future work. Throughout the above experimental results, we point out that the impact of rebuffering on abandonment rate is more than six times higher than pre-roll ads in YouTube.

2) **Bitrate switching**: Some researchers [16]–[20] investigate the impact of bitrate changes on video QoE. They claim that providing a bitrate as high as possible does not necessarily lead to the highest QoE [17]. They agree on the fact that it is difficult to model a quantitative metric that takes account of all the bitrate switching events, such as the number of bitrate switches.
3) **Rebuffering vs. bitrate switching:** We compare the impact of rebuffering and bitrate switching on video abandonment rates. We note that it is difficult to compare both events under the same criteria. For example, we observe that multiple rebufferings can appear as a cluster (Figure 8) while the bitrate is seldom to change multiple times in the short period of time. As we described earlier, it would be very complicated to create a proper model to reflect all the factors (e.g., intervals among events and duration for each event) for evaluation. In order to avoid this complexity, we take into account only the single events for the comparison. We classify the dataset into two groups. In the first group, we collect a total of 9,577 video sessions where the viewers experienced a single rebuffering event without any bitrate changes and ads in the middle of the playback. The second group includes a total of 4,991 video sessions that experienced a single bitrate change with no rebufferings and ads while the video was being played. We use the same methodology to calculate the abandonment rate, and observe 1.2% for bitrate change and 3.9% for a rebuffering on average.

Few studies [16], [21] have actually investigated the comparison between rebuffering and bitrate switching. They conclude that the rebufferings must be absolutely avoided during playback, and the bitrate changes may degrade video QoE when the bitrate switches involving low bitrates. Our solution can quantify the abandonment rates for both events from a large number of samples in YouTube, showing that a single rebuffering event causes abandonment rate three times higher than a single bitrate change.

4) **Multiple playback events:** Throughout prior subsections, we analyzed the impact of rebufferings and bitrate changes on abandonment rates separately. But, both events are not independent, instead correlated in ABR streaming (i.e., a player degrades bitrates to avoid rebufferings). In Figure 14, we combine these two factors together for an analysis of abandonment rate. Overall, the results show that more viewers generally abandon videos as rebuffering and bitrate change ratios increase in the middle of a playback.

We claim that monitoring rebuffering ratio and bitrate changes over playback can be a good reference to improve user engagement while a video is being played. We suggest to implement these metrics in an ABR player, and use the outputs for bitrate selection along with current playlist buffer level and available network throughput estimated by the bandwidth estimator (Figure 1). For instance, let’s suppose that the current bitrate change ratio is 5 and rebuffering ratio is 0.08. Our goal is to maintain the abandonment rate lower than 10%. In this case, the player may conservatively increase the bitrate (with enough data stored in the buffer and high bandwidth available in the network) unless the bitrate change ratio becomes above 10 (Figure 14). It may hold the decision for a certain amount of time if increasing the bitrate causes the estimated abandonment rate higher than 10%. As another example, the player may track rebuffering ratio when inserting ads in the middle of a playback. In this case, let’s consider the video ad as a single rebuffering event during a download. The idea is to set up the

![Figure 14: Abandonment rates (%) with multiple playback events length of mid-roll ads based on the current rebuffering ratio. So if the ratio is very low, for example, the viewer is more tolerant to such pre-roll ads than rebufferings, with the experimental results showing the impact of start-up latency on abandonment rates, six times lower than the impact of rebufferings in YouTube.](image)

**Finding 1:** Our measurements show that a start-up latency in YouTube is mostly caused by pre-roll ads. We conclude that the viewers were more tolerant to such pre-roll ads than rebufferings, with the experimental results showing the impact of start-up latency on abandonment rates, six times lower than the impact of rebufferings in YouTube.

**Finding 2:** We observe that viewers are more likely to abandon videos with multiple rebufferings, compared to a single rebuffering event although the rebuffering ratio is the same. We also confirm that viewers prefer constant bitrate to increasing bitrate during playback, and frequent bitrate increase can lead to an abandonment rate more than four times higher than a case with no bitrate changes.

**Finding 3:** According to our analysis, a single rebuffering event causes abandonment rate three times higher than a single bitrate change.

**Finding 4:** We show that monitoring rebuffering and bitrate change ratios is a proper metric to quantify video abandonment rates for short videos such as YouTube. We suggest to implement these metrics in an ABR player to improve user engagement especially when inserting video ads or changing bitrates in the middle of a playback.

**VI. RELATED WORK**

Google video quality report [22] provides statistics of YouTube played bitrates along with local ISPs. The methodology is to calculate goodput at server-side and rate the ISP performance by comparing the measurement with pre-defined thresholds. However, the output does not provide any QoE factors from the perspective of viewers, such as how often...
they experience bitrate changes and rebufferings. Dobrian et al. [23] in Conviva monitored various playback events directly from video players. The methodology used for data collection is similar to our approaches. But, our platform allows viewers and video service providers to monitor various playback statistics in real time via our QoE monitoring system. In addition, we suggest simpler metrics (e.g., monitoring rebuffering ratio and bitrate change ratio over playback time) that can be implemented at video players to estimate abandonment rates. We believe that the measurement can be a good reference to improve ABR streaming (i.e., when changing bitrates or inserting ads in the middle of a playback).

For analyzing network performance issues such as page loading times, Dhawan et al. [24] introduce Fathom, a browser-based network measurement platform. As a proof of concept, they have built a Firefox extension that allows web sites or other parties to program network measurements using JavaScript. Shafig et al. [11] monitored the video abandonment by inspecting video packets, but the method is not simple compared to our web browser plug-in that can detect such abandonments directly from video players. Hossefeld et al. [13] investigate the impact of rebuffering patterns (i.e., how many and often rebufferings appear during playback) on video QoE. Ni et al. [19] study how viewers experience bitrate changes at different amplitudes and frequencies. Using HTTP DASH, Mok et al. [17] show that viewers prefer to gradually change bitrate instead of a sudden switch among bitrates during playback. Most work has been done with a relatively small number of dataset. Unlike prior approaches, our solution provides a cost-effective way to collect a large number of samples and confirms various QoE metrics with evidence from large video streaming services such as YouTube.

VII. CONCLUDING REMARKS

We introduced YouSlow as a new video QoE analysis tool for video QoE. This lightweight web browser plug-in can detect various playback events for an analysis of video QoE. Our experimental results show that monitoring rebuffering ratio and bitrate changes over playback time is a proper QoE metric to analyze abandonment rates for short videos such as YouTube. As key observations, we find that a start-up latency mostly caused by pre-roll ads have less impact on abandonment rates, compared to rebufferings. Further, our analysis shows that viewers prefer constant bitrate to increasing bitrate during playback, and a single rebuffering causes abandonment rate three times higher compared to a single bitrate change. We believe that our proposed QoE metrics and experimental results give us an insight to improving ABR heuristics embedded in ABR players and enhancing viewing experiences.

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