Requet: Real-Time QoE Metric Detection for Encrypted YouTube Traffic

CRAIG GUTTERMAN, Electrical Engineering, Columbia University
KATHERINE GUO, Nokia Bell Labs
SARTHAK ARORA, Computer Science, Columbia University
TREY GILLILAND, Computer Science, Columbia University
XIAOYANG WANG, Nokia Bell Labs
LES WU, Nokia Bell Labs
ETHAN KATZ-BASSETT, Electrical Engineering, Columbia University
GIL ZUSSMAN, Electrical Engineering, Columbia University

As video traffic dominates the Internet, it is important for operators to detect video Quality of Experience (QoE) in order to ensure adequate support for video traffic. With wide deployment of end-to-end encryption, traditional deep packet inspection-based traffic monitoring approaches are becoming ineffective. This poses a challenge for network operators to monitor user QoE and improve upon their experience. To resolve this issue, we develop and present a system for **RE**al-time **QU**ality of experience metric detection for **E**ncrypted **T**raffic, **Requet**, that is suitable for network middlebox deployment. *Requet* uses a detection algorithm we develop to identify video and audio chunks from the IP headers of encrypted traffic. Features extracted from the chunk statistics are used as input to a Machine Learning (ML) algorithm to predict QoE metrics, specifically, *buffer warning* (low buffer, high buffer), *video state* (buffer increase, buffer decay, steady, stall), and *video resolution*. We collect a large YouTube dataset consisting of diverse video assets delivered over various WiFi and LTE network conditions to evaluate the performance. We compare *Requet* with a baseline system based on previous work and show that *Requet* outperforms the baseline system in accuracy of predicting buffer low warning, video state, and video resolution by 1.12×, 1.53×, and 3.14×, respectively.

CCS Concepts: • **Information systems** → **Multimedia streaming**; • **Networks** → *Network performance analysis*; • **Computing methodologies** → *Classification and regression trees*;

Additional Key Words and Phrases: Machine Learning, HTTP Adaptive Streaming

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Authors' addresses: Craig Gutterman, Electrical Engineering, Columbia University; Katherine Guo, Nokia Bell Labs; Sarthak Arora, Computer Science, Columbia University; Trey Gilliland, Computer Science, Columbia University; Xiaoyang Wang, Nokia Bell Labs; Les Wu, Nokia Bell Labs; Ethan Katz-Bassett, Electrical Engineering, Columbia University; Gil Zussman, Electrical Engineering, Columbia University.

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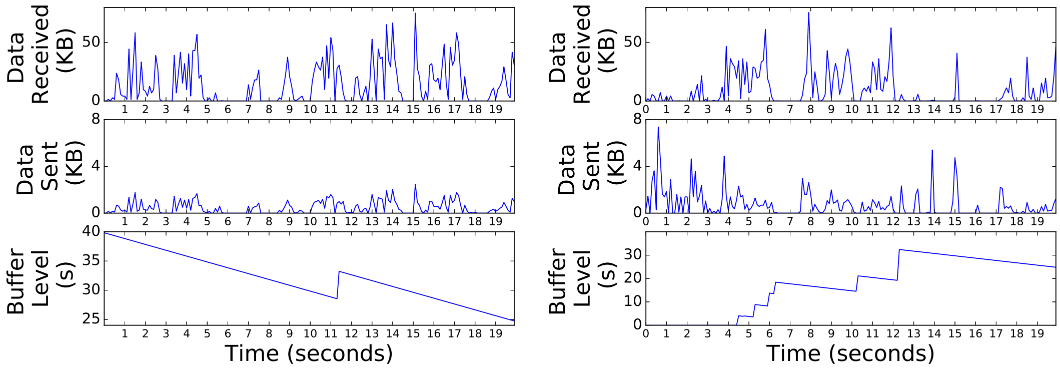


Fig. 1. Amount of data received (KB), amount of data sent (KB), and buffer level (sec) for two sessions over a 20 sec window (100 ms granularity): (a) 720p, (b) 144p.

1 INTRODUCTION

Video has monopolized Internet traffic in recent years. Specifically, the portion of video over mobile data traffic is expected to increase from 60% in 2016 to 78% by 2021 [2]. Content providers, Content Delivery Networks (CDNs), and network *operators* are all stakeholders in the Internet video sector. They want to monitor user video Quality of Experience (QoE) and improve upon it in order to ensure user engagement. Content providers and CDNs can measure client QoE metrics, such as video resolution by using server-side logs [8, 21]. Client-side measurement applications can accurately report QoE metrics such as player events and video quality levels [36, 50].

Traditionally, Deep Packet Inspection (DPI) enabled operators to examine HTTP packet flows and extract video session information to infer QoE metrics [7, 12]. However, to address security and privacy concerns, content providers are increasingly adopting end-to-end encryption. A majority of YouTube traffic has been encrypted since 2016 [4] with a combination of HTTPS (HTTP/TLS/TCP) [9, 18, 40] and QUIC (HTTP/QUIC/UDP) [15, 25]. Similarly, since 2015 Netflix has been deploying HTTPS for video traffic [10]. In general, the share of encrypted traffic is estimated to be over 80% in 2019 [5].

Although the trend of end-to-end encryption does not affect client-side or server-side QoE monitoring, it renders traditional DPI-based video QoE monitoring ineffective for operators. Encrypted traffic still allows for viewing packet headers in plain text. This has led to recent efforts to use Machine Learning (ML) and statistical analysis to derive QoE metrics for operators. These works either provide offline analysis for the entire video session [16, 37] or online analysis using both network and transport layer information with separate models for HTTPS and QUIC [35].

Previous research developed methods to derive network layer features from IP headers by capturing packet behavior in both directions: *uplink* (from the client to the server) and *downlink* (from the server to the client) [26, 35, 37]. However, determining QoE purely based on IP header information is inaccurate. To illustrate, Fig. 1 shows a 20 sec portion from two example sessions from our YouTube dataset, described in §4, where each data point represents 100 ms. Both examples exhibit similar patterns in the downlink direction while in the uplink direction, traffic spikes are much higher in Fig. 1(b) than in Fig. 1(a). However, Fig. 1(a) shows a 720p resolution with the buffer decreasing by 15 secs, whereas Fig. 1(b) shows a 144p resolution with the buffer increasing by 20 secs.

Given this challenge, our objective is to design features from IP header information that utilize patterns in the video streaming algorithm. In general, video clips stored on the server are divided into a number of *segments* or *chunks* at multiple resolutions. The client requests each chunk by individually sending an HTTP GET request to the server. Existing work using chunks either infers QoE for the entire session [31] rather than in real-time, or lacks insight on chunk detection mechanisms from network or transport layer data [16, 28, 42].

To improve on existing approaches that use chunks, we develop **Requet**, a system for **RE**al-time **QU**ality of experience metric detection for **E**ncrypted **T**raffic designed for traffic monitoring in middleboxes by operators. *Requet* is devised for real-time QoE metric identification as chunks are delivered rather than at the end of a video session. *Requet* is designed to be memory efficient for middleboxes, where the memory requirement is a key consideration. Fig. 2 depicts the system diagram for *Requet* and necessary components to train the QoE models as well as evaluate its performance. *Requet* consists of the ChunkDetection algorithm, chunk feature extraction, and ML QoE prediction models. The data acquisition process involves collecting YouTube traffic traces (*Trace Collection*) and generating ground truth QoE metrics as labels directly from the player (*Video Labeling*). Packet traces are fed into *Requet*'s ChunkDetection algorithm to determine audio and video chunks. The chunks are then used during the *Feature Extraction* process to obtain chunk-based features. The chunk-based features from the training data along with the corresponding QoE metrics are used to generate QoE prediction models. For evaluation, traffic traces from the testing dataset are fed into the trained QoE models to generate predicted QoE metrics. Accuracy is measured by comparing the predicted QoE metrics and the ground truth labels.

Recent studies have shown that (i) stall events have the largest negative impact on end user engagement and (ii) higher average video *playback bitrate* improves user engagement [8, 17]. Motivated by these findings, *Requet* aims to predict the current video resolution and events that lead to QoE impairment *ahead of time*. This allows operators to proactively provision resources [13, 39]. *Requet* predicts low buffer level which allows operators to provision network resources to avoid stall events [26]. *Requet* predicts four video states: buffer increase, buffer decay, steady, and stall. Furthermore, *Requet* predicts current video resolution during a video session in real-time. Specifically, *Requet* predicts video resolution on a more granular scale (144p, 240p,360p, 480p, 720p, 1080p), while previous work predicts only two or three levels of video resolution for the entire video session [16, 31, 35].

We make the following contributions:

- Collect packet traces of 60 diverse YouTube video clips resulting in a mixture of HTTP/TLS/TCP and HTTP/QUIC/UDP traffic. The traces are collected in two distinct settings with the first set collected from a laptop web browser over WiFi networks from three service providers, two in the United States and one in India, and the second set collected from the YouTube App on an Android mobile device over LTE cellular networks. This is in contrast to most prior works which rely on simulation or emulation [26, 35, 46] (see §4).
- Design *Requet* components
  - Develop ChunkDetection, a heuristic algorithm to identify video and audio chunks from IP headers (see §3).
  - Analyze the correlation between audio and video chunk metrics (e.g., chunk size, duration, and download time) and various QoE metrics, and determine fundamental *chunk-based* features useful for QoE prediction. Specifically, design features based on our observation that audio chunk arrival rate correlates with the video state (see §5).
  - Develop ML models to predict QoE metrics in real-time: buffer warning, video state, and video resolution (see §6).
- Evaluate *Requet* performance
  - Demonstrate drastically improved prediction accuracy using chunk-based features versus baseline IP layer features commonly used in prior work [26, 35, 37, 47]. For the setting of a web browser over WiFi networks, *Requet* predicts low buffer warning with 92% accuracy, video state with 84% accuracy, and video resolution with 66% accuracy, representing an

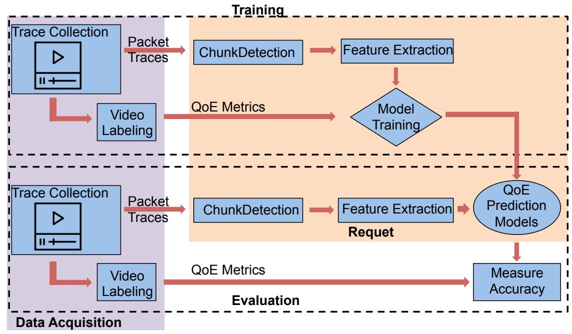


Fig. 2. System Diagram: Data acquisition and *Requet* components: ChunkDetection, feature extraction, and QoE prediction models.

improvement of 1.12×, 1.53×, and 3.14×, respectively, over the existing baseline system. Furthermore, *Requet* delivers a 91% accuracy in predicting low (144p/240p/360p) or high resolution (480p/720p/1080p) in both the web browser over WiFi setting and the YouTube App over LTE setting (see §6).

– Demonstrate that *Requet* trained in a lab environment works on unseen clips with varying lengths from different operators in multiple countries. This evaluation is more diverse than prior work [16, 26, 35, 46] (see §6).

2 BACKGROUND & PROBLEM STATEMENT

2.1 Adaptive BitRate Streaming Operation

A majority of video traffic over the Internet today is delivered using HTTP Adaptive Streaming (HAS) with its dominating format being Dynamic Adaptive Streaming over HTTP (DASH) or MPEG-DASH [45, 52]. In Adaptive BitRate (ABR), a video *asset* or *clip* is encoded in multiple resolutions. Encoding is controlled by multiple parameters and a given resolution is associated with a fixed setting for quantization, which is then coarsely related to an average bandwidth determined by the source video. A clip with a given resolution is then divided into a number of *segments* or *chunks* of variable length, a few seconds in playback time [33]. Typically video clips are encoded with Variable Bitrate (VBR) encoding and are restricted by a maximum bitrate for each resolution. An audio file or the audio track of a clip is usually encoded with Constant Bitrate (CBR). For example some of the YouTube audio bitrates are 64, 128, and 192 Kbps [49].

At the start of the session, the client retrieves a manifest file which describes the location of chunks within the file containing the clip encoded with a given resolution. There are many ABR variations across and even within video providers [33]. ABR is delivered over HTTP(S) which requires either TCP or any other reliable transport [19]. The ABR algorithm can use concurrent TCP or QUIC/UDP flows to deliver multiple chunks simultaneously. A chunk can either be video or audio alone or a mixture of both.

2.2 Video States and Playback Regions

The client employs a *playout buffer* or *client buffer*, whose maximum value is *buffer capacity*, to temporarily store chunks to absorb network variation. To ensure smooth playback and adequate *buffer level* the client requests a video clip chunk by chunk using HTTP GET requests, and dynamically determines the resolution of the next chunk based on network condition and buffer status.[1]

When the buffer level is below a low threshold, the client requests chunks as fast as the network can deliver them to increase the buffer level. We call this portion of ABR operation the *buffer filling* stage. In this stage, buffer level can increase or decrease. Once the buffer level reaches a high

[1]The field of ABR client algorithm design is an active research area [24, 34].

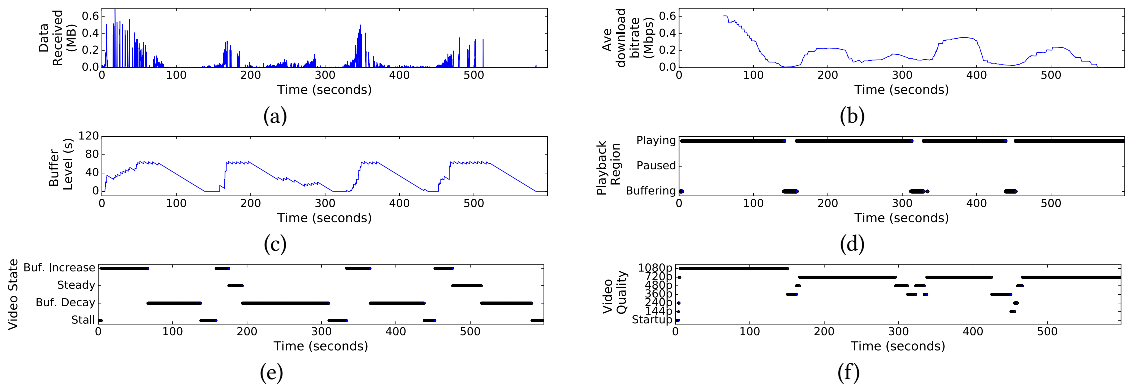


Fig. 3. Behavior of a 10-min session in 100 ms windows: (a) amount of data received (MB), (b) average download bitrate (Mbps) over the past 60 sec, (c) buffer level, (d) playback region, (e) video state, (f) video resolution.

threshold, the client aims to maintain the buffer level in the range between the threshold and buffer capacity. One example of a client strategy is to request chunks as fast as they are consumed by the playback process, which is indicated by the video *playback bitrate* for the chunk [47]. We call this portion the *steady state* stage. The playback *stalls* when the buffer is empty before the end of the playback is reached. After all chunks have been downloaded to the client buffer, there is no additional traffic and the buffer level decreases. From the perspective of buffer level, an ABR session can experience four exclusive *video states*: *buffer increase*, *buffer decay*, *steady state*, and *stall*.

Orthogonally, from the perspective of YouTube video playback, a session can contain three exclusive *regions*: *buffering*, *playing*, and *paused*. Buffering region is defined as the period when the client is receiving data in its buffer, but video playback has not started or is stopped. Playing region is defined as the period when video playback is advancing regardless of buffer status. Paused region is defined as the period when the end user issues the command to pause video playback before the session ends. In playing region, video state can be in either buffer increase, decay, or steady state.

Fig. 3 shows the behavior of a 10-min session from our dataset in §4 in each 100 ms window with (a) the amount of data received (MB), (b) download throughput (Mbps) for the past 60 sec, (c) buffer level (sec), (d) occurrence of three playback regions, (e) occurrence of four video states, and (f) video resolution. At the start of the session and after each of the three stall events, notice that video resolution slowly increases before settling at a maximum level.

2.3 QoE Metrics and Prediction Challenges

This subsection describes the QoE metrics that we reference and the challenges in predicting these metrics. We focus on metrics that the operator can use to infer user QoE impairments in real-time. Specifically, we use three QoE metrics: *buffer warning*, *video state* and *video quality*. We do not focus on start up delay prediction, as it has been extensively studied in [26, 31, 35].

The first QoE metric we aim to predict is the current *video state*. The four options for video state are: buffer increase, buffer decay, stall, or steady state. This metric allows for determining when the video level of the user is in the ideal situation of steady state. Video state also recognizes occurrences of buffer decay and stall events, when the operator may want to allocate more resources towards this user given that there are enough resources and the user is not limited by the data plan.

The *buffer warning* metric is a binary classifier for determining if the buffer level is below a certain threshold $BuffWarning_{\mathrm{thresh}}$ (e.g., under 20 sec). This enables operators to provision resources in real-time to avoid potential stall events before they occur. For example, at a base station or WiFi AP, ABR traffic with buffer warning can be prioritized.

Another metric used is the current *video resolution*. Video encoders consider both resolution and target video bitrate. Therefore, it is possible to associate a lower bitrate with a higher resolution. One can argue bitrate is a more accurate indicator of video quality. However, higher resolutions for a given clip often result in higher bitrate values. The YouTube client reports in real-time resolution rather than *playback bitrate*. Therefore, we use resolution as an indicator of video quality.

ABR allows the client to dynamically change resolution during a session. Frequent changes in resolution during a session tend to discourage user engagement. Real-time resolution prediction enables detection of resolution changes in a session. However, this prediction is challenging as *download bitrate* to video resolution does not follow a 1-to-1 mapping. In addition, a video chunk received by the client can either replace a previous chunk or be played at any point in the future. Under the assumption that playback typically begins shortly (in the order of seconds) after the user requests a clip, one can associate the average download bitrate with video quality, since higher quality requires higher bitrate for the same clip. However, this is not true in a small time scale necessary for real-time prediction. Network traffic reveals the combined effect of buffer trend (increase or decay) and video *playback bitrate* which correlates to resolution. During steady state, video's *download bitrate* is consistent with playback bitrate. However, when a client is in non-steady state, one cannot easily differentiate between the case in which a higher resolution portion is retrieved during buffer decay state (Fig. 1(a)), and the case in which a lower resolution portion is retrieved during buffer increase state (Fig. 1(b)). Both of these examples exhibit similar traffic patterns, however the behavior of QoE metrics is dramatically different.

3 CHUNK DETECTION

The fundamental delivery unit of ABR is a chunk [27]. Therefore, identifying chunks instead of relying on individual packet data can capture important player events. Our approach is to explore the fundamental principle of HAS which is to transmit media in the unit of video and audio chunks. The behavior of chunks over the transmission network is directly associated with the HAS protocol and behavior of the client buffer. This method is able to derive QoE metrics as long as one can (i) detect chunks and (ii) build models associating IP level traffic information with client buffer level. Therefore, this method is immune to changes to HAS as long as chunks can be detected from IP level traffic.

Specifically, the occurrence of a chunk indicates that the client has received a complete segment of video or audio, resulting in increased buffer level in playback time. An essential component of *Requet* in Fig. 2 is its ChunkDetection algorithm to identify chunks from encrypted traffic traces. Features are extracted from the chunks and used as the input to the ML QoE prediction models. Existing work using chunks either studies per-session QoE metrics [31] instead of predicting QoE metrics in real-time, or lacks insight in chunk detection mechanisms [16, 28, 42]. In general, there are two approaches of identifying chunks, (i) identify a packet with non-zero payload from the client to the server as an HTTP request [31] and (ii) use an idle period (e.g., 900 ms is used to separate chunks in a flow of Netflix traffic [30]).

In this section, we first describe metrics capturing chunk behavior. We then develop ChunkDetection, a heuristic algorithm using chunk metrics to identify individual audio and video chunks from IP level traces. *Requet* uses ChunkDetection to detect chunks from multiple servers simultaneously regardless of the use of encryption or transport protocol. It relies purely on source/destination IP address, port, protocol, and payload size from the IP header.

3.1 Chunk Metrics

We define the following metrics for a chunk based on the timestamp of events recorded on the end device (as shown in Fig. 4).

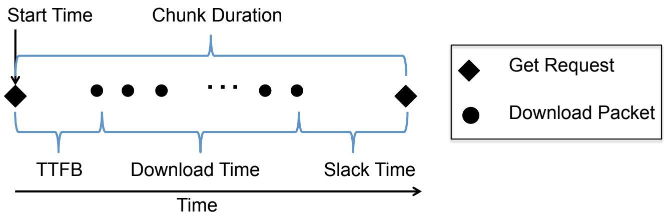


Fig. 4. Definition of chunk metrics (video or audio).

Algorithm 1 Audio Video Chunk Detection Algorithm

```
procedure ChunkDetection
    Initialize Audio⃗ and Video⃗ for each IP flow I
    for each uplink packet p with IP flow I do
        if uplink(p) and (packetlength(p) > GET_thresh then)
            c ← [GetTimestamp, GetSize, DownStart,
            DownEnd, GetProtocol, I]
            AVflag ← DetectAV(c)
            if AVflag == 0 then
                Append c to Audio⃗
            else if AVflag == 1 then
                Append c to Video⃗
            else
                Drop c
            GetTimestamp ← time(p)
            GetSize ← packetlength(p)
            DownFlag ← 0
        if downlink(p) and (packetlength(p) > Down_thresh then)
            if DownFlag == 0 then
                DownFlag = 1
                DownStart ← time(p)
            DownEnd ← time(p)
            DownSize+ = packetlength(p)
```

- **Start_Time** - The timestamp of sending the HTTP GET request for the chunk.
- **TTFB** - Time To First Byte, defined as the time duration between sending an HTTP GET request and the first packet received after the request.
- **Download_Time** - The time duration between the first received packet and the last received packet prior to the next HTTP GET request.
- **Slack_Time** - The time duration between the last received packet and the next HTTP GET request.
- **Chunk_Duration** - The time duration between two consecutive HTTP GET requests. The end of the last chunk in a flow is marked by the end of the flow. Note that a different concept called "segment duration" is defined in standards as playback duration of the segment [6]. For a given chunk, Chunk_Duration equals "segment duration" only during steady state.
- **Chunk_Size** - The amount of received data (sum of IP packet payload size) during Download_Time from the IP address that is the destination of the HTTP GET request marking the start of the chunk.

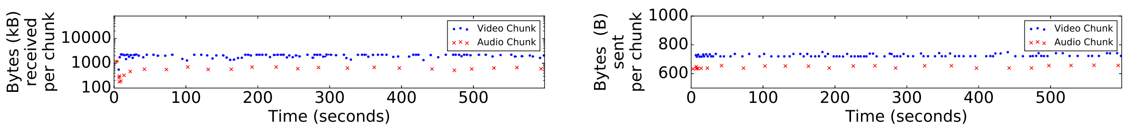
Note, for any chunk, the following equation holds: Chunk_Duration = sum(TTFB, Download_Time, Slack_Time).

3.2 Chunk Detection Algorithm

We explore characteristics of YouTube audio and video chunks. Using the web debugging proxy Fiddler [3], we discovered that audio and video are transmitted in separate chunks, and they do not overlap in time for either HTTPS or QUIC. For both protocols we notice at most one video or audio chunk is being downloaded at any given time. Each HTTP GET request is carried in one IP

Table 1. Chunk Notation

Symbol	Semantics
GET_{thresh}	pkt length threshold for request (300 B)
$Down_{\text{thresh}}$	pkt length threshold for downlink data (300 B)
$GetTimestamp$	timestamp of GET request
$GetSize$	pkt length of GET request
$DownStart$	timestamp of first downlink packet of a chunk
$DownEnd$	timestamp of last downlink packet of a chunk
$DownSize$	sum of the payload of downlink packets of a chunk
$GetProtocol$	IP header protocol field
DetectAV	sorts chunk into audio chunk, video chunk or no chunk based on $GetSize$, $DownSize$, $GetProtocol$
$\vec{Audio}$	audio chunks for an IP flow
$\vec{Video}$	video chunks for an IP flow



(a) (b)

Fig. 5. Individual video/audio chunks in a 10-min session with highest resolution (V:1080p, A:160kbps). (a) Chunk Size, (b) Get Request Size.

packet with IP payload size above 300 B. Smaller uplink packets are HTTP POST requests regarding YouTube log events, or TCP ACKs.

We propose a heuristic chunk detection algorithm in Algorithm 1 using notations in Table 1. ChunkDetection begins by initializing each IP flow with empty arrays for both audio and video chunks. This allows for the chunk detection algorithm to collect chunks from more than one server at a time.

ChunkDetection initially recognizes any uplink packet with a payload size above 300 B as an HTTP GET request (line 4). This threshold may vary depending on the content provider. For YouTube, we note that GET requests over TCP are roughly 1300 bytes, while GET requests over UDP are roughly 700 bytes. For each new GET request the $GetTimestamp$, and $GetSize$, are recorded (lines 14-16). After detecting a GET request in an IP flow, chunk size is calculated by summing up payload size of all downlink packets in the flow until the next GET is detected (lines 17-22). The last downlink packet in the group between two consecutive GET requests marks the end of a chunk download. The chunk download time then becomes the difference in timestamp between the fist and the last downlink packet in the group. [2]

Once the next GET is detected, ChunkDetection records $GetTimestamp$, $GetSize$, download start time $DownStart$, download end time $DownEnd$, the protocol used $GetProtocol$, download size $DownSize$, and the IP flow I of the previous chunk (line 5). This allows for the calculation of chunk duration and slack time using the timestamp of the next GET. GET request size and chunk size are used in DetectAV (line 7) to separate data chunks into audio chunks, video chunks, or background traffic (lines 8-11). DetectAV uses the heuristic that HTTP GET request size for audio chunks is slightly smaller than request size for video chunks consistently. Figs. 5 and 6 plot the HTTP GET request size and subsequent audio/video chunk size in a high (1080p) and a low (144p) resolution session, respectively. It is evident from Figs. 5(b), and 6(b) that the HTTP GET request size for

[2]ChunkDetection does not flag TCP retransmission packets, therefore can overestimate chunk size when retransmission happens. ChunkDetection also assumes chunks do not overlap in time in a given IP flow. If it happens, the individual chunk size can be inaccurate, but the average chunk size over the period with overlapping chunks is still accurate.

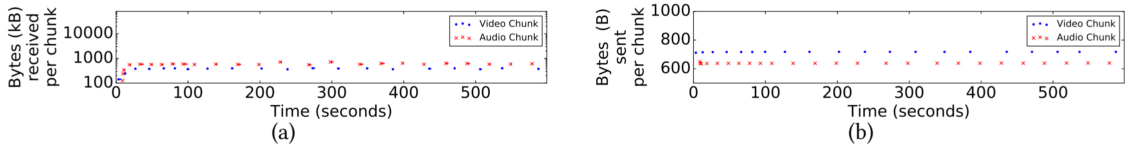


Fig. 6. Individual video/audio chunks in a 10-min session with lowest resolution (V:144p, A:70kbps). (a) Chunk Size, (b) Get Request Size.

audio chunks is slightly smaller than that for video chunks. Through the examination of encrypted YouTube HTTP GET requests for video and audio using Fiddler, we discover that this difference is due to the additional fields used in HTTP GET requests for video content which do not exist for audio content. Furthermore, as can be seen in Fig. 5(a), the video chunk size at higher resolution levels is consistently larger than the audio chunk size. However, as can be seen in Fig. 6(a), the video chunk size at lower resolution levels can be similar to or even smaller than the audio chunk size. We can conservatively set the low threshold for chunk size to be 80 KB for our dataset. Furthermore, if download size is too small (< 80 KB), DetectAv recognizes that the data is neither an audio or video chunk, and the data is dropped (lines 12-13). This allows ChunkDetection to ignore background YouTube traffic.

4 DATA ACQUISITION

As shown in Fig. 2, data acquisition provides data for training and evaluation for *Requet* QoE prediction models, including traffic trace collection, derivation of QoE metrics as ground truth labels associated with traffic traces. We describe additional details about the publicly available dataset in Appendix B. We collect data in two distinct settings, one using YouTube from a browser on a laptop over WiFi networks (*"Browser-WiFi"*), and the other using YouTube App on an Android smartphone over LTE cellular networks (*"App-LTE"*). We name the datasets Browser-WiFi and App-LTE, respectively. The data is collected over two different time periods to illustrate *Requet*'s performance, since the underlying protocol of YouTube may vary on different devices, over different networks, and over time [33].

4.1 Trace Collection from Browser over WiFi

For the first set of experiments, we design and implement a testbed (shown in Fig. 7(a)) to capture a diverse range of YouTube behavior over WiFi. We watch YouTube video clips using the Google Chrome browser on a Macbook Air laptop. We connect the laptop to the Internet via an Access Point (AP) using IEEE 802.11n. A shell script simultaneously runs Wireshark's Command Line Interface, Tshark [1], and a Javascript Node server hosting the YouTube API.

The YouTube IFrame API environment collects information displayed in the "Stats for Nerds" window. From this API we monitor: video playback region ('Playing', 'Paused', 'Buffering'), playback time since the beginning of the clip, amount of video that is loaded, and current video resolution. From these values we determine the time duration of the portion of the video clip remaining in the buffer. We collect information once every 100 ms as well as during any change event indicating changes in video playback region or video resolution. This allows us to record any event as it occurs and to keep detailed information about playback progress.

We have two options to collect network level packet traces in our setup, on the end device or on the WiFi AP. Collecting traces at the AP would limit the test environment only to a lab setup. Therefore, we opt to collect traces via Wireshark residing on the end device. This ensures that the YouTube client data is synchronized with Wireshark traces and the data can be collected on public and private WiFi networks. Our traces record packet timestamp, size, as well as the 5-tuple for IP-header (source IP, destination IP, source port, destination port, protocol). Our dataset contains

(a) (b)

Fig. 7. Experimental setup for our trace collection. (a) WiFi experiments conducted in the lab on a laptop, (b) Cellular experiments on an android cellphone.

delivery over HTTPS (9% GET requests) and QUIC (91% GET requests). We do not use any transport level information. In addition, we record all data associated with a Google IP address. The IP header capture allows us to calculate total number of packets and bytes sent and received by the client in each IP flow during a given time window.

To generate traces under varying network conditions, we run two categories of experiments: *static* and *movement*. For static cases, we place the end device in a fixed location for the entire session. However, the distance from the AP varies up to 70 feet or multiple rooms away. For movement cases, we walk around the corridor (up to 100 feet) in our office building with the end device, while its only network connection is through the same AP.

We select 60 YouTube clips representing a wide variety of content types and clip lengths. Each clip is available in all 6 common resolutions from YouTube, namely 144p, 240p, 360p, 480p, 720p and 1080p. We categorize them into four groups, where groups A and B are medium length clips (8 to 12 min), C are short clips (3 to 5 min), and D are long clips (25-120 min). Table 2 lists the number of unique clips in the group, along with the length of each clip and the session length, that is, the duration for which we record the clip from its start.

For group A, we collect 425 sessions in both static (over 300) and movement cases (over 100) in a lab environment in our office building. All remaining experiments are conducted in static cases. For clips in group B, we collect traces in an apartment setting in the US (set B_1 with 60 sessions) and in India (set B_2 with 45 sessions) reflecting different WiFi environments. We collect traces in set C and D from the lab environment, where each set contains more than 25 sessions. Overall, there are over 10 sessions for each clip in group A and B and 6 sessions for each clip in group C and D.

Clips in both groups A and B range from 8 to 12 min in length. In each session we play a clip and collect a 10-min trace from the moment the client sends the initial request. We choose this range of length in order for the client to experience buffer increase, decay and steady state. Shorter clips with a length close to buffer capacity (e.g., 2 min) can sometimes never enter steady state, even when given abundant network bandwidth. In general, when there is sufficient bandwidth to support the clip's requirement, a clip can be delivered in its entirety before the end of the playback happens. On the contrary, when available network bandwidth is not enough to support the clip's requirement, a clip may experience delayed startup and even stall events.

We collect traces over 6 months from Jan. through June 2018, with video resolution selection set to *"auto"*. This means the YouTube client is automatically selecting video resolution based on changes in network conditions. For each session, we set an initial resolution to ensure that all resolution levels have enough data points.

Each group includes a diverse set of clips in terms of activity level. It ranges from low activity types such as lectures to high activity types such as action sequences. This fact can be seen in the wide range of video bitrates for any given resolution. Fig. 8 shows the average playback bitrate for each video resolution for each clip in our dataset. All clips are shown in scatter plots, while clips in group A are also shown with box plots.[3] One can see that the average video playback bitrate spans

[3]For all box plots in the paper, the middle line is the median value. The bottom and top line of the box represents Q1 (25-percentile) and Q3 (75-percentile) of the dataset respectively. The lower extended line represents $Q1 - 1.5IQR$, where IQR is the inner quartile range (Q3-Q1). The higher extended line represents $Q3 + 1.5IQR$.

Table 2. Clip distribution in our dataset.

Group	Clip Length	Session Length	No. of Unique Clips
A	$8-12$ min	10 min	40
B	$8-12$ min	10 min	10
C	$3-5$ min	5 min	5
D	$25-120$ min	30 min	5

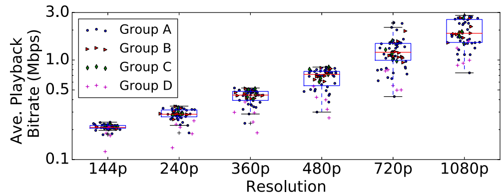


Fig. 8. Average playback bitrate vs. video resolution for clips in our dataset. Clips in all four groups are shown in scatter plots, while clips in group A are also shown with box plots.

overlapping regions. Therefore, this cannot provide a perfect indication of the video resolution even if the entire session is delivered with a fixed resolution.

In our dataset, we notice that YouTube buffer capacity varies based on video resolution. For example, it is roughly 60, and 120 sec for 1080p and 144p, respectively.

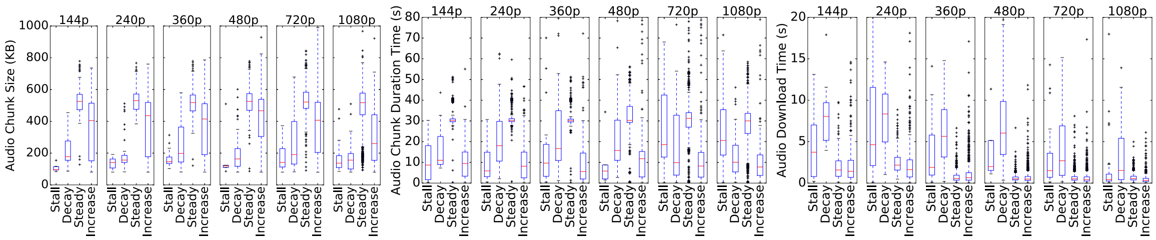
We collect data for each YouTube video session in the Chrome browser as the sole application on the end device. We record all packets between the client and any Google server. The client contacts roughly 15 to 25 different Google servers per session. We examine the download throughput (see Fig. 3(a) and 3(b) for example) further by looking at the most commonly accessed server IP addresses for each session sorted by the total bytes received. Our observation is that, during a session, the majority of traffic volume comes from a single to a few servers.

4.2 Trace Collection from YouTube Android App over Cellular

Testing on a mobile device connected to a laptop computer allows us to easily connect to cellular networks which enables testing outside of a lab environment over a cellular network. For the second set of experiments, we design and implement a data acquisition environment (shown in Fig. 7(b)) to capture YouTube video playback statistics and encrypted network packet data on an Android device over a cellular network. We use a rooted Motorola Moto G6 smartphone connected to the Internet via Google Fi's cellular networks. A shell script autonomously sets up the testing environment using Android Debugging Bridge (ADB), collects packet data through tcpdump, and collects video playback statistics through the YouTube Android App.

The YouTube App allows for collection of video playback statistics through its "Stats for Nerds" window. This window allows us to easily monitor audio and video resolution, buffer health, and video playback region ("Playing", "Paused", and "Buffering"). We copy the information provided by that window every 1 sec to a clipboard log using ClipStack which can then be easily exported from the device.

Because we do not have access to data going through the cellular network, we opt to collect network traffic data on the phone using tcpdump for Android. We conduct tests in multiple cellular conditions such as in a car driving on the highway, on a Columbia University shuttle bus around upper Manhattan, in a backpack walking up and down the streets of New York City, and during lectures. We collect this set of cellular data over 7 months from June through Dec. 2019. Again, we use the 40 unique medium length clips in group A (8 to 12 min in length). The dataset consists of over 250 video sessions with resolution ranging from 144p to 1080p.



(a) (b) (c)

Fig. 9. Chunk metrics for all audio chunks in set A in Browser-WiFi setting. (a) chunk size, (b) chunk duration, (c) download time.

5 REQUET ML FEATURE DESIGN

We develop the ML *QoE metric prediction models* for *Requet* by using packet traces and associated ground truth labels (§4). We describe in detail in Appendix A our heuristic algorithm for the video state labeling process to associate each time window with one of the four video states: buffer increase, buffer decay, steady state, and stall. As shown in Fig. 2, *Requet* uses its ChunkDetection component (§3) to convert traces into chunks, followed by its Feature Extraction component to extract associated features.

We develop ML models using Random Forest (RF) to predict user QoE metrics [23]. We build the RF classifier in Python using the sklearn package. We configured the model to have 200 estimators with the entropy selection criterion and the maximum number of features per tree set to auto. We choose RF for the following reasons. (i) ML classification algorithms based on decision trees have shown better results in similar problems [16, 30, 35, 37, 47, 51] with RF showing the best performance among the class [30, 47, 51]. (ii) On our dataset, Feedforward Neural Network and RF result in roughly equal accuracy. (iii) RF can be implemented with simple rules for classification in real-time, well suited for real-time resource provisioning in middleboxes.

Each session in our dataset consists of (i) IP header trace and (ii) QoE metric ground truth labels generated by our video labeling process in data acquisition (§4). *Requet*'s ChunkDetection (§3.2) transforms the IP header trace into a sequence of chunks along with the associated chunk metrics (§3.1). The goal of *Requet* QoE models is to predict QoE metrics using chunk metrics. To train such ML models, it is critical to capture application behavior associated with QoE metrics using chunk-based features. In this section, we analyze chunk behavior in our dataset (§5.1), explore how to capture such behavior in chunk-based features (§5.2), and explain how to generate baseline features used in prior work that are oblivious to chunk information (§5.3).

5.1 Chunk Analysis

We apply the ChunkDetection algorithm (Algorithm 1) of *Requet* to all sessions from the 40 clips in set A in our dataset in both Browser-WiFi and App-LTE settings.

We examine the correlation between various chunk metrics (audio or video, chunk size, chunk duration, *effective rate* which we define as chunk size over chunk duration, TTFB, download time, and slack time) to QoE metrics (buffer level, video state, and resolution). In most cases of our dataset, for a given session, audio and video chunks are transmitted from one server. However, in some cases audio and video traffic comes from different servers. In other cases, the server switches during a session. These findings are consistent with existing YouTube traffic studies [36].

5.1.1 Chunk Analysis in Browser-WiFi Setting. We list the distribution of audio and video chunks along with video state at the end of chunk download in Table 3. Most of the chunks arrive during steady or buffer increase states. An extremely small fraction (4% audio and 9% video) are associated with stall or buffer decay states. They represent two possible scenarios: (i) bandwidth is limited and

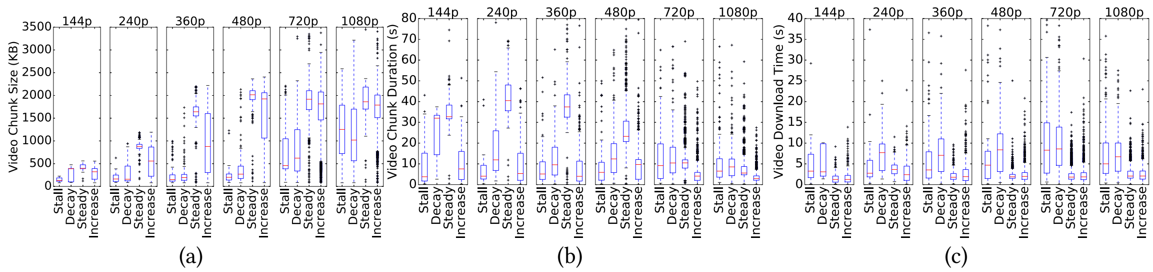


Fig. 10. Chunk metrics for all video chunks in set A in Browser-WiFi setting. (a) chunk size, (b) chunk duration, (c) download time.

Table 3. % of chunks in each state (Set A Browser-WiFi).

Resolution	Video State			
	Stall	Decay	Steady	Increase
Audio	1.2	2.8	40.9	55.1
Video	3.7	5.9	47.6	42.8

Table 4. % of chunks in each state (Set A App-LTE).

Resolution	Video State			
	Stall	Decay	Steady	Increase
Audio	2.7	4.0	52.3	41.0
Video	3.6	6.8	49.6	40.0

there are not enough chunks arriving to increase buffer level substantially or (ii) buffer is about to transition into increase state.

Figs. 9 and 10 show the box plots for chunk duration, size, and download time for audio and video chunks respectively. Each plus sign represents an outlier. TTFB reflects the round trip time from the client to the server, and has a median value of 0.05 sec. This accounts for a tiny portion of chunk duration (median value ≥ 5 sec). We can safely simplify the relationship between various chunk metrics to (slack time = chunk duration - download time). Notice that slack time and effective rate are derivable from chunk duration, size, and download time. The latter three are the key metrics used in our feature selection for ML models.

Audio is encoded with CBR, however our examination of HTTP requests using Fiddler [3] reveal that in the four video states (steady, buffer increase, decay and stall), audio chunk size decreases in the same order. This implies that audio chunk playback time also decreases in the same order. This behavior is consistent across all resolution levels (Fig. 9(a)) and indicates that audio chunk size exhibits a strong correlation with video state. Across all resolution levels, Fig. 9(b) shows median audio chunk duration in steady and buffer increase state is roughly 30 and 10 sec respectively, but does not exhibit clear pattern in stall and buffer decay states. Fig. 9(c) shows audio chunk download time in steady and buffer increase states are similar in value, both smaller than that of stall state, which is smaller than that of buffer decay state. The longer download time is an indication that the network bandwidth is limited. This is a useful insight that current bandwidth alone can not reveal. For example, a specific throughput can be associated to a low resolution with the buffer increasing or a higher resolution with the buffer decreasing. All three audio chunk metrics are clearly correlated with video state.

Fig. 10 shows video chunk statistics. There is a large overlap across different resolutions and video states in chunk size (Fig. 10(a)) and chunk duration (Fig. 10(b)). It reveals that without knowing video state, it would be difficult to determine video resolution, chunk size, and chunk duration. For example, these statistics are very similar for a 240p chunk in buffer increase state and a 720p chunk in buffer decay. Using audio chunk statistics to identify video state is critical in separating these two cases.

For video chunks, our examination of HTTP requests using Fiddler also shows that for a clip with a given resolution, steady state chunk size is larger than that in the remaining three states. Fig. 10(a) further shows that median video chunk size increases as resolution increases from 144p

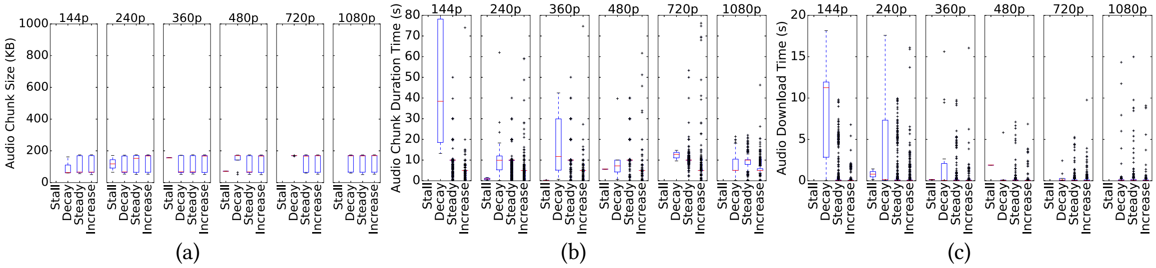


Fig. 11. Chunk metrics for all audio chunks in set A in App-LTE setting. (a) chunk size, (b) chunk duration, (c) download time.

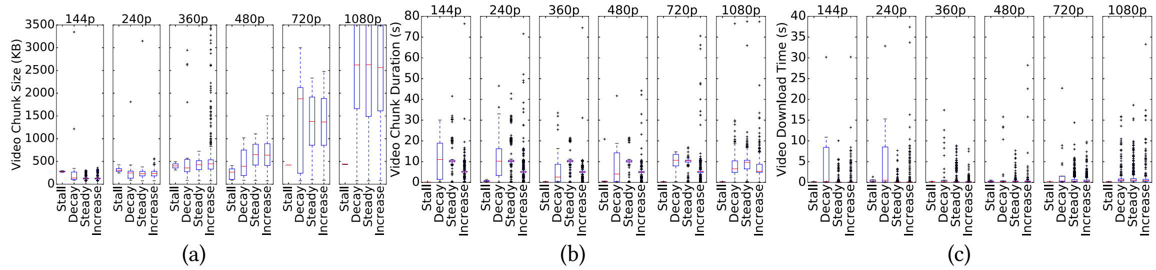


Fig. 12. Chunk metrics for all video chunks in set A in App-LTE setting. (a) chunk size, (b) chunk duration, (c) download time.

to 480p and stays roughly the same around 2 MB from 480p to 1080p. Fig. 10(b) shows median chunk duration in steady state is similar for 144p, 240p, and 360p, in the range of 35 – 45 sec, and decreases from 25 sec for 480p to 5 sec for 1080p. To obtain a higher effective rate for higher resolutions the chunk size levels off, but to compensate chunk duration decreases. Fig. 10(c) shows that median chunk download time exhibits larger values in stall or buffer decay state, smaller and similar values in steady or buffer increase state. This is expected as with limited bandwidth, a session may experience buffer decay or even stall. Both buffer decay and stall periods exhibit larger chunk download times. However, during buffer increase, retrieving smaller chunks faster than steady state results in similar download time as steady state. During steady and buffer increase state, chunk size and duration combined provide some indication of resolution levels. However, during stall and buffer decay state, no indication can be easily seen from the three metrics.

To summarize, our key observations are as follows: (i) Without knowing video state it would be difficult to differentiate between the two cases: (a) Higher resolution clip in buffer decay and (b) Lower resolution clip in buffer increase. (ii) Audio chunk statistics exhibit strong association with video state. (iii) Video chunk size increases and eventually levels off as resolution increases. At the same time, video chunk duration is higher for lower resolution levels and decreases as resolution level increases.

5.1.2 Chunk Analysis in App-LTE Setting. Similar to the Browser-WiFi setting, most of the chunks in the App-LTE setting arive during steady or buffer increase states.

For the App-LTE setting, Figs. 11 and 12 show the box plots for chunk duration, size, and download time for audio and video chunks respecitvely. Each plus sign represents an outlier.

Across all resolution levels, Fig. 11(b) shows that median audio chunk duration is roughly 10 sec in steady state and 5 sec in buffer increase state. However, there is no clear pattern in stall or buffer decay states. Audio chunk size is consistent across all resolution levels (Fig. 11(a)) and is usually around 70KB or 170KB. These patterns are considerably different from the Browser-WiFi setting in Fig. 9.

Fig. 12 shows video chunk statistics in the App-LTE setting. Again, the pattern is drastically different than the pattern in the Browser-WiFi setting in Fig. 10. Fig. 12(a) shows that across different states in the same resolution, the chunk size is much more consistent. In addition there is a clear pattern of increasing chunk size as the resolution increases. The video chunk duration results (Fig. 12(b)) show that video chunks arrive roughly every 10 sec during steady state and roughly every 5 sec during buffer increase state. This video chunk arrival behavior is similar to that of the audio chunks in the same dataset. Fig. 12(c) shows, with a fixed resolution, median video chunk download times exhibit larger values in stall or buffer decay state, and smaller values in steady or buffer increase state. This is expected, since with a fixed chunk size, a larger chunk duration is associated with limited bandwidth, which can cause a session to deplete its buffer (enter buffer decay state) or even stall.

5.2 Chunk-based Features in *Requet*

Requet identifies chunks using Algorithm 1 executed over all flows during a YouTube session. For each audio or video chunk, it records the following seven chunk metrics: protocol used to send the GET request, start time, TTFB, download time, slack time, chunk duration, and chunk size. However, it does not record the server IP address from which the chunk is delivered to the end device as it has no relationship with our QoE metrics.

Results from §5.1 show that the most important metrics for both audio and video are chunk size, duration, and download time. Chunk arrival is not a uniform process in time and therefore, the number of chunks in a time window vary. This would require a variable number of features. Instead, *Requet* uses statistics of chunk metrics in different time windows. Specifically, for the 20 windows representing the immediate past 10, 20, ..., 200 sec, it records total number of chunks, average chunk size and download time for each time window, resulting in 60 features each for audio and video, and a total of 120 features.[4] Regarding video resolution, *Requet* only makes predictions upon receiving a video chunk. Therefore, beyond the 120 features, it further includes the 7 features associated with the video chunk. By only collecting data on a per chunk basis, *Requet* requires a minimal amount of storage of 7 fields per chunk in the middlebox. Figs. 11(b) and 12(b) show that chunks in the dataset arrive on average once every 5 sec. The sliding window based features in *Requet* make it ideal for middleboxes with a memory requirement of 1016 bytes for the 127 features (assuming each feature requires a maximum of 8 bytes).

5.3 Baseline Features

For the baseline system, we remove *Requet*'s ChunkDetection algorithm in Fig. 2 and the associated features. We replace *Requet* and design a baseline system with a set of features that are commonly used in prior work [26, 35, 37, 47]. Specifically, we select features that are used in more than one of these prior works and use time window based features. We collect basic IP level features in terms of flow duration, direction, volume (total bytes), burstiness, as well as transport protocol. For each 100 ms window, we calculate the total number of uplink and downlink packets and bytes, and include a one-hot vector representation of the transport protocols used for each IP address.[5] The five features for transport protocol are QUIC, TCP with TLS, TCP without TLS, no packets in that interval, or other. After examining the total downlink bytes of the top 20 flows in a session in our dataset, we decide to include traffic from the top 3 servers in our feature set. The remaining flows have significantly smaller traffic volume and therefore represent background traffic in a session

[4]We use the past 200sec history as YouTube buffer rarely increases beyond 3 min.

[5]In natural language processing, a one-hot vector is a $1xN$ matrix (vector) used to distinguish each word in a vocabulary from every other word in the vocabulary. The vector consists of 0s in all cells with the exception of a single 1 in a cell used uniquely to identify the word. In our case, each IP address is treated as a word.

and do not deliver video or audio traffic. By doing so, we effectively eliminate the traffic that is unrelated to our QoE metrics. In addition, we include the total number of uplink/downlink bytes and packets from the top 20 servers for the session.

We calculate the average throughput and the total number of packets in the uplink and downlink direction during a set of time intervals to capture recent traffic behavior. Specifically, we use six intervals immediately proceeding the current prediction window, and they are of length 0.1, 1, 10, 60, 120, and 200 sec.

Furthermore, during these six windows, we record the percentage of 100 ms slots with any traffic in uplink and downlink separately. These two features are added to determine how bursty the traffic is during the given time window. In addition to the four features for the total network traffic for all servers contacted during the session, the features for each of the top three servers are:

- total bytes in past 100 ms in uplink/downlink
- total number of packets in past 100 ms in uplink/downlink
- transport protocol (5 features)
- for each of the windows of length 1, 10, 60, 120, and 200 sec:
  - average throughput in uplink/downlink
  - total number of packets in uplink/downlink
  - % of 100 ms slots without any traffic in uplink/downlink

To summarize, for each time window, there are up to $4 + 3 \times (4 + 5 + 5 \times 6) = 121$ features for the baseline system.

6 EVALUATION

We evaluate the performance of *Requet* in both the Browser-WiFi setting and the App-LTE setting. For the Browser-WiFi setting we compare the accuracy in predicting each QoE metric of *Requet* versus the baseline system. Both systems predict the current QoE metrics every 5 sec, except for *Requet* which predicts resolution every chunk. Since the collected network traffic transport payload is encrypted, we are unable to evaluate *Requet* against previous works that use deep packet inspection. Data collected as described in §4 is used for training, validation, and testing. Out of the four sets of traces in our dataset (§4.1), we use group A, the largest one to train both systems to predict each QoE metric in real-time. We follow the same testing procedure to evaluate the performance of *Requet* in the App-LTE setting. We then compare the performance differences of *Requet* in both settings.

We extend the evaluation of *Requet* in the Browser-WiFi setting by testing *Requet* on smaller groups B, C, and D. Subsequently, we use groups B_1 and B_2 to determine how training in the lab environment works on clips with similar length but with different service providers and wireless network conditions. B_1 and B_2 are experiments in residential WiFi settings in the US and India, respectively. We also use group A as the training set for evaluating shorter clips (group C) and longer clips (group D) in the same lab environment as group A.

For group A, we conduct 4-fold cross validation on the 40 clips. Specifically, we divide the 40 clips into four exclusive sets each with ten unique clips. In each fold, we first train a model for each QoE metric using RF with features from 30 clips (three of the four sets). We then test the model on the ten clips from the remaining set. We report each model's average performance over the four folds.

The buffer warning model produces two prediction possibilities. It indicates whether the buffer level is below the threshold $BuffWarning_{\text{thresh}}$ or not. The video state model produces four states and the resolution model produces six resolution levels.

Table 5. Buffer warning performance with data in group A.

Type	Baseline Browser-WiFi		*Requet* Browser-WiFi		*Requet* App-LTE	
	Precision	Recall	Precision	Recall	Precision	Recall
BfW	51.0	11.1	79.0	68.7	88.4	79.7
NBfW	86.0	98.1	94.1	96.5	98.5	99.2
Accuracy	84.9		92.0		97.8	

Table 6. Video state performance with data in group A.

Type	Baseline Browser-WiFi		*Requet* Browser-WiFi		*Requet* App-LTE	
	Precision	Recall	Precision	Recall	Precision	Recall
Stall	31.1	7.6	70.4	51.9	92.2	86.3
Buf. Decay	32.0	16.3	78.0	78.7	65.7	25.2
Buf. Increase	64.1	57.6	80.2	84.2	88.1	95.8
Steady	57.6	80.2	90.7	92.2	89.6	90.2
Accuracy	55.4		84.2		88.2	

We report *accuracy* of each model as the ratio of the number of correct predictions over total number of predictions. For each label a model predicts, we further report: (i) *precision* defined as the ratio of true positives to total positives, that is, the percentage of correct predictions out of all positive predictions of a label, and (ii) *recall* defined as the ratio of correct predictions to total true occurrences of a label, that is, the percentage of a label correctly predicted.

6.1 Buffer Warning Prediction

The first metric we examine is buffer warning. We set the threshold for buffer level warning, $\mathit{BuffWarning}_{\text{thresh}}$, to be 20 secs. This provides ample time to provision enough bandwidth before an actual stall occurs.

For this metric, each time window in our dataset is labeled with either "no buffer warning" (NBfW) or "buffer warning" (BfW). In group A, significantly more chunks are labeled with NBfW (84%) than BfW (16%). The results in Table 5 show that in the Browser-WiFi setting both baseline and *Requet* perform well for this task, with accuracy reaching 85% and 92%, respectively. We see that precision and recall for NBfW are higher than those for BfW in both baseline and *Requet*. Given the current label is BfW, *Requet* provides significantly higher probability of predicting BfW correctly with recall of 68% over 11% for the baseline. This is because *Requet* uses chunk features to detect the case when no chunks have recently arrived. However, it is difficult for the baseline system to identify such cases due to the lack of chunk detection. For example, baseline can not differentiate packets as being part of a chunk or background traffic.

In the App-LTE setting, *Requet* shows slightly improved performance compared to Browser-WiFi. *Requet* achieves a recall of 79.9% for BfW and 99.2% for NBfW. This results in a total accuracy of 97.8%. For the Browser-WiFi dataset, the download time and TTFB of the most recent chunk, the video chunk count and the average video chunk size of a variety of windows are significant features that are used in the RF model for buffer warning prediction. For the App-LTE dataset, the download time and TTFB of the most recent chunk, the video chunk count, and the audio chunk count of a variety of windows are significant features that are used in the RF model for buffer warning prediction.

6.2 Video State Prediction

The results of video state prediction are shown in Table 6. In the Browser-WiFi setting, *Requet* achieves overall accuracy of 84%, compared to 55% for baseline, representing a 53% improvement. *Requet* also outperforms baseline in precision and recall for each state.

Table 7. Video resolution performance with data in group *A*.

Type	Baseline Browser-WiFi Precision	Baseline Browser-WiFi Recall	*Requet* Browser-WiFi Precision	*Requet* Browser-WiFi Recall	*Requet* App-LTE Precision	*Requet* App-LTE Recall
144p	13.0	7.6	80.6	79.9	87.8	86.2
240p	14.6	10.1	68.7	64.3	74.0	81.8
360p	14.1	9.9	49.2	64.4	74.0	79.4
480p	24.7	33.3	64.9	63.8	73.7	57.2
720p	24.5	30.3	60.6	54.5	80.3	83.4
1080p	22.2	20.1	75.0	76.9	91.9	89.4
Accuracy	21.8		66.9		80.6	

Stall, buffer decay, buffer increase and steady state appear in 3.7%, 5.9%, 42.8% and 47.6% of chunks in group *A* respectively (Table 3). The precision and recall for both systems increase in the same order of stall, buffer decay, buffer increase and steady.

However, baseline achieves below 40% in precision and recall for both the stall and buffer decay states. This implies that during these two states, network traffic does not have a significant pattern for baseline to discover. Furthermore, during steady state there can be gaps of 30 sec or longer. A long gap also occurs when buffer is in decay state. Baseline features cannot separate buffer decay from steady state.

Examination of the *Requet* model reveals that audio chunk count for each 20 sec window is an important feature to predict video state. For example, if there are a few audio chunks in the past 20 sec it is likely that buffer is increasing, and if there are no audio chunks in the past 120 sec it is likely to be in stall state. This explains the relatively high performance of *Requet* .

In the App-LTE setting, *Requet* achieves an overall accuracy of 88.2%. Compared to the Browser-WiFi dataset, *Requet* in the App-LTE setting achieves an improved performance in predicting the stall state, but is worse in predicting buffer decay.

For the App-LTE dataset the download time and TTFB of the most recent chunk, and the number of video chunks in the time range from 60 to 200 sec are significant features that are used in the RF model for state prediction. For the Browser-WiFi dataset the download time and TTFB of the most recent chunk, the number of video chunks in the time range from 60 to 200 sec, and the average chunk size are significant features that are used in the RF model for state prediction.

6.3 Video Resolution Prediction

It is extremely challenging for baseline to predict video resolution even with history of up to 200 sec. Overall accuracy is only 22%, slightly better than randomly picking one out of six choices.

As seen in Fig. 8, there is a large overlap of average playback bitrates of video clips of different resolutions due to varying activity levels in the video content. Without any knowledge about the content of the video or the video state, it is extremely difficult if not impossible to associate a chunk given its playback bitrate with the resolution it is encoded with. Furthermore, without knowing video state there is a large overlap in video chunk size and chunk duration across resolutions as seen in Fig. 10.

By using both audio and video chunks, *Requet* achieves a 66% accuracy for predicting resolution (six levels) in the Browser-WiFi setting. This result demonstrates that *Requet* is able to enhance video resolution prediction. By narrowing down the options in resolution to three: small (144p/240p), medium (360p/480p), and large (720p/1080p), *Requet* achieves an accuracy of 87%. If the number of options is reduced to two: small (144p/240p/360p) and large (480p/720p/1080p) the accuracy improves to 91%.

The accuracy of *Requet* in the App-LTE setting is 80.6%. *Requet* in the App-LTE setting has improved performance compared to in the Browser-WiFi setting in predicting all resolutions except

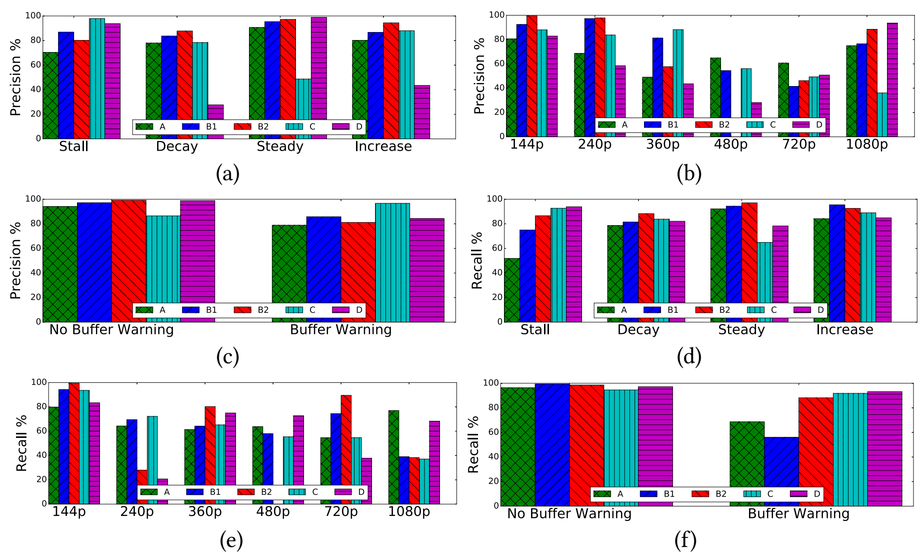


Fig. 13. Accuracy of *Requet* models trained with group *A*. (a) Precision of video state, (b) Precision of video resolution, (c) Precision of stall warning, (d) Recall of video state, (e) Recall of video resolution, (f) Recall of stall warning.

480p, where it has difficulties differentiating 480p from 360p. This can be caused by the dataset having more data points during 360p as well as having similar video chunk sizes for these two resolutions.

For both datasets, the most important features are those features related to the most recent chunk as well as the average video chunk size.

6.4 Performance Comparison of Browser-WiFi vs. App-LTE

The performance of *Requet* in the App-LTE setting is considerably greater than in the Browser-WiFi setting. As shown in Tables 5, 6, and 7, the accuracy for predicting buffer warning, video state, and video resolution in the Browser-WiFi setting is 92.0%, 84.2%, and 66.9%, respectively. While the accuracy for predicting buffer warning, video state, and video resolution in the App-LTE setting is 97.8%, 88.2%, and 80.6%, respectively. The only exception to this is when predicting the buffer decay state, the accuracy is higher in the Browser-WiFi setting.

There are two potential reasons for the higher accuracy in the App-LTE setting. First, across different states in the same resolution, the chunk size is more consistent in the App-LTE setting. Second, the network conditions are more stable in the App-LTE setting, due to generally good service coverage in our test area. However, in the Browser-WiFi setting, artificially varying network conditions are created from movement experiments during the data collection stage. More stable network conditions naturally lead to less variation in video states once steady state is entered.

6.5 Extended Test over WiFi Networks

Up to this point we have reported results from our systems trained with part of group *A* and tested on different clips in group *A* in both the Browser-WiFi setting and the App-LTE setting. Next, we use group *A* in the Browser-WiFi setting as the training data for *Requet* and evaluate with groups B_1, B_2, C, and D. We test *Requet* on 10 clips from groups B_1 and B_2 for residential WiFi settings in the US and India, respectively, to see how they perform on unseen clips of similar length and unseen WiFi environments. In addition, we use the same lab WiFi environment in group *A*, to test *Requet* on 5 clips of shorter length of 5 min in group *C* and longer length of 25 min in group

D. Fig. 13 reports the average precision and recall of these four tests along with the 4-fold cross validation results from group A.

Depending on the environment and QoE metric, performance of these extended sets of tests either improves or deteriorates compared with results from group A reported earlier in this section. For example, groups B_1, B_2, and C have improved precision and recall in predicting stall and buffer decay states. Group D shows lower precision in predicting buffer decay, but higher recall for both stall and buffer decay. Improved precision and recall results appear for predicting buffer threshold warning.

Accuracy for video resolution varies from experiment to experiment. Surprisingly, group B_2 has the highest overall accuracy of 70% when training with group A. This is in part due to that there were zero 480p events collected in group B_2. This resolution level has lower precision than 144p, 240p, and 1080p (see Table 7), and is extremely difficult for the other test sets to predict as well.

Most precision and recall results for other sets are better than group A with a few exceptions. This could be due to the fact that group A includes movement experiments, while the other groups only contain static ones. A video session naturally exhibits different behavior in different types of environments. In addition, we plan to improve our prediction models by studying how the imbalance in data samples impacts the precision and recall of each model.

7 RELATED WORK

Traditional traffic monitoring systems rely on DPI to understand HTTP request and reply messages. The systems use meta-data to understand ABR and infer video QoE metrics. The MIMIC system estimates average bitrate, re-buffering ratio and bitrate switches for a session by examining HTTP logs [32]. Comparatively, BUFFEST builds ML classifiers to estimate buffer level based either on the content of HTTP requests in the clear or on unencrypted HTTPS requests by a trusted proxy [26]. HighSee identifies HTTP GET requests and builds a linear Support Vector Machine (SVM) [14] model to identify audio, video, and control chunks to separate audio, video and control flows [20].

For encrypted traffic, proposals fall into two categories. The first category builds session models offline by detecting HTTP requests as in eMIMIC [31], while the second category builds ML models to predict QoE metrics either offline or online.

Offline Models: The offline approach uses entire video session traffic to generate features to classify the session into classes. YouQ classifies a session into two to three QoS classes [37]. The system in [16] builds models to roughly put a session into three categories in terms of stall events ("non-stall", "0-1 stalls", or "2-or-more stalls"), or three classes based on average quality level. The system in [38] captures IP level traffic information (which is suitable for both TLS and QUIC traffic) and feeds ML models to predict per-session Mean Opinion Score (MOS) (2 or 3 classes), longest resolution ("sd" vs. "hd"), and stalling occurrences ("yes" vs. "no"). Using simulation, [48] builds ML models to predict average bitrate, quality variation, and three levels of stall ratio (no, mid, severe) for entire sessions using post processing. Comparatively, [29] classifies a session into two categories (with or without stall events) based on cell-related information collected at the start of a video session.

Focusing on the newly proposed Network Data Analytics Function in the 5G architecture, [43] associates network QoS metrics with the MOS for each video session using ML models. Rather than using actual network traces, the evaluation of the ML models is purely based on simulation.

Online Models: The online approach uses traffic from the past time window in the session to generate features to predict QoE metrics specific to that time window. ViCrypt [44] develops ML models to predict stall events both in real-time and for the entire video session based on network level information for separate TCP and UDP flows. On the other hand, [51] builds ML models to purely predict video resolution in real-time using network level information as features. The focus of the study is on feature selection and benchmarking of different ML models. Similarly, [30] simply focuses on prediction of buffer level using features based on network level information. It only predicts two states – "buffering" and "stable" and discards any transition period in between (that is, without including these data in training or testing of ML models), while *Requet* predicts video state based on buffer status in much finer granularity (with four exclusive states: buffer increase, buffer decay, steady state and stall) without discarding any data. The system in [35] develops features based on both network and transport level information in a 10 sec time window to build separate classifiers for HTTPS and QUIC traffic to infer startup delay (below or above a given threshold), stall event occurrence, and video quality level ("low" and "high"). This system uses features based on packet level information and collects data for time windows of 100 ms. This has a relatively large memory requirement compared to *Requet* which only requires network data collected on a per chunk basis.

The system in [11] uses network and application level features to infer startup delay and resolution. Similar to *Requet* , they also identify video chunks.

Flow Identification: Identifying video flows from encrypted traffic is orthogonal to the QoE detection problem for given ABR flows. It is an example of the broad encrypted traffic classification problem. The Silhouette system [28] detects video chunks (also named Application Data Units) from encrypted traffic in real-time for ISP middleboxes using video chunk size, payload length, download rate threshold values. The real-time system in [41] identifies Netflix videos using TCP/IP header information including TCP sequence numbers. This approach relies on a "finger print" database built from a large number of video clips hosted by Netflix. The finger print is unique for each video title, therefore it is ineffective in classifying new video titles not previously seen. The system in [47] classifies an encrypted Youtube flow every 1sec interval into HAS or non-HAS flows in real-time. For a HAS flow, it further identifies the buffer states of the video session into filling, steady, depleting and unclear. The high accuracy to predict buffer state is partly due to the fact that the entire dataset contains only 3 clips with multiple sessions for each clip. This system also uses a feature based on the standard deviation of packet size, which is not feasible for implementation in middleboxes due to the memory requirement.

8 CONCLUSION AND FUTURE WORK

We present *Requet*, a system for **RE**al-time **QU**ality of experience metric detection for **E**ncrypted **T**raffic. We focus on three QoE metrics (1) buffer warning, (2) video state, and (3) video quality, as they are crucial in allowing network level resource provisioning in real-time. We design a video state labeling algorithm to automatically generate ground truth labels for ABR traffic data.

Requet consists of the ChunkDetection algorithm, chunk feature extraction, and ML QoE prediction models. Our evaluation using YouTube traffic collected over WiFi networks demonstrates *Requet* using chunk-based features exhibit significantly improved prediction power over the baseline system using IP-layer features.

We demonstrate that the *Requet* QoE models trained on one set of clips exhibit similar performance in different network environments with a variety of previously unseen clips with various lengths. In addition, by testing with both the Browser on WiFi and the YouTube Application on LTE settings we validate that *Requet* performs well even for different streaming algorithms.

A current limitation of *Requet* is that it is based on YouTube and needs to be trained separetly for each streaming algorithm. Therefore, one direction of our future work includes building a generic model for a wide range of networks and client algorithms for ABR. We plan to evaluate additional services such as Disney+ and Netflix. Another direction of our future work includes using software defined networking to utilize *Requet* and investigate the QoE improvements achieved via resource scheduling. We aim to study the joint effect of operator optimization and content provider video optimization mechanisms.

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Algorithm 2 Video State Labeling Algorithm

procedure VideoStateLabeling
  Initialize δ, ϵ, T_{smooth}, T_{slope}
  for every t **do**
    Calculate $\hat{B}_t \leftarrow median[B_{t-T_{\text{smooth}}}, \ldots, B_{t+T_{\text{smooth}}}]$
    Calculate $m_t \leftarrow \frac{\hat{B}_{t+T_{\text{slope}}} - \hat{B}_{t-T_{\text{slope}}}}{2T_{\text{slope}}}$
    if $\hat{B}_t \leq \delta$ **then**
      $State_t \leftarrow$ Stall
    else if $-\epsilon \leq m_t \leq \epsilon$ and $\hat{B}_t > Buff_{\text{SS}}$ **then**
      $State_t$ = Steady State
    else if $m_t < 0$ **then**
      $State_t \leftarrow$ Buffer Decay
    else
      $State_t \leftarrow$ Buffer Increase
  $SmoothState(State)$

Table 8. Notation Summary

Symbol	Semantics	Defaults
δ	Stall threshold	0.08 sec
ϵ	Buffer slope boundary for Steady State	$0.15\ \frac{sec}{sec}$
T_{smooth}	Time window for smoothing buffer	15 sec
T_{slope}	Time window to determine buffer slope	5 sec
$Buff_{\text{SS}}$	Minimum buffer level to be in steady state	10 sec
Thr_{SS}	Minimum time window to stay in steady state	15 sec
$MinTime_{\text{SS}}$	Time window to look for quick changes out of steady state	10 sec
$MinTime_{\text{stall}}$	Time window to look for quick changes out of stall state	10 sec

A VIDEO STATE LABELING

A goal for predicting video QoE in real-time inside the network is to enable real-time resource provisioning to prevent stalls and decreases in video resolution. To enable this prediction, accurate labeling of video state is critical. The four exclusive video states (buffer increase, decay, stall and steady state) accurately capture the variations in buffer level. They can be used in combination with actual buffer level to predict dangerous portions of ABR operation that may lead to QoE degradation. For example, when the buffer level is close to 0, a stall event is likely to happen in the near future. Increasing network capacity for the session may prevent a stall.

As shown in §2, playback regions reported by the client ignore buffer level changes, and cannot be used to generate video states. Prior work uses manual examination which is time consuming and can be inaccurate [47]. We opt to automate the process by developing the definition of video states based on buffer level variation over time followed by our video state labeling algorithm. We define the four video states as follows:

(1) **Buffer Increase:** Buffer level is increasing. It has a slope greater than ϵ per sec over time window T_{slope}.
(2) **Steady State:** Buffer level is relatively flat. The slope of buffer level is between $-\epsilon$ and $+\epsilon$ $\frac{sec}{sec}$ over time window T_{slope}. To be in steady state the slope needs to be in this range for greater than Thr_{SS} sec.
(3) **Buffer Decay:** Buffer level is decreasing with a slope less than $-\epsilon$ $\frac{sec}{sec}$ over time window T_{slope}.
(4) **Stall:** Buffer level is less than or equal to δ.

We execute our video state labeling algorithm in Algorithm 2 for each time instance t when buffer information is recorded (every 100 ms) to determine video state for a session according to our definition.

As a chunk arrives at the client, buffer level increases by chunk length in sec. During playback, buffer level decreases by 1 sec for every sec of playback. Looking at short windows or the wrong point of a window would incorrectly determine that buffer is decreasing. We use a smoothing function to derive a more accurate buffer slope. Specifically, we use a moving median filter over a window around t defined by $[t - T_{\text{smoooth}}, t + T_{\text{smooth}}]$. We examine the rate of change of the buffer slope over a window around t defined by $[t - T_{\text{slope}}, t + T_{\text{slope}}]$.

In order to avoid rapid changes of stall state, we set δ to 0.08 sec. This value ensures that small variations in and out of stall state are consistently labeled as being in stall state. If the buffer level is above $Buff_{\text{SS}}$ and has a slope between $-\epsilon$ and ϵ $\frac{sec}{sec}$, then we label it as steady state. If these specifications are not met and the slope is negative, we set the state to buffer decay. If the slope is positive, we set the state to buffer increase.

To ensure that video state does not change rapidly due to small fluctuations of buffer level, we use an additional heuristic of $SmoothState$: steady state has to last longer than Thr_{SS}. This allows chunks with playback time longer than this value to arrive at the client. If there are changes out of and then back into stall state that last less than $MinTime_{\text{stall}}$ we consider the entire period as stall state. Similarly, if there are changes out of and then back into steady state that last less than $MinTime_{\text{SS}}$, we consider the entire period steady state. For clarity, we list all symbols in Table 8, as well as the values that we find to work the best empirically for our dataset.

B DATASET INFO

This appendix provides a description of the dataset acquired in §4, used for *Requet* chunk detection in §3, and for evaluation in §6.

The dataset can be found in a Github Repository (https://github.com/Wimnet/RequetDataSet). The dataset is divided into 5 *group folders* for data from groups A, $B1$, $B2$, C, D, along with a summary file named 'ExperimentInfo.txt' for the entire dataset. Each line in the file describes an experiment using the following four attributes: (a) experiment number, (b) video ID, (c) initial video resolution, and (d) length of experiment in seconds.

A group folder is further divided into two subfolders, one for PCAP files, and the other for txt files. Each experiment is described by a PCAP file and a txt file. The PCAP file with name in the form of (i) *'baseline_{date}_exp_{num}.pcap'* is for an experiment where the end device is static for the entire duration whereas a file with name in the form of (ii) *'movement_{date}_exp_{num}.pcap'* is for an experiment where the end device movement occurs during the experiment. The txt file names end with *'merged.txt'*. The txt file contains data colletect from YouTube API and summary of PCAP trace for the experiment.

In each *'merged.txt'* file, data is recorded for each 100 ms interval. Each interval is represented as: [*Relative Time*, # Packets Sent, # Packets Received, # Bytes Sent, # Bytes Received, [Network Info 1], [Network Info 2], [Network Info 3], [Network Info 4], [Network Info 5], ... , [Network Info 25], [*Playback Info*]].

Relative Time marks the end of the interval. *Relative Time* is defined as the time since the Javascript Node server hosting the YouTube API is started. Relative Time for the 0^{th} interval is defined as 0 sec. It is updated in intervals of 100 ms. TShark is called prior to the Javascript Node server. Therefore, the 0^{th} interval contains Wireshark data up to the start of the Javascript Node server.

Network Info i is represented as: [IP_Src, IP_Dst, Protocol, # Packets Sent, # Packets Received, # Bytes Sent, # Bytes Received] for each interval. IP_Src is the IP address of the end device. The top 25 destination IP addresses in terms of total bytes sent and received for the entire session are recorded.

For each i of the top 25 IP_Dst addresses, the Protocol associated with the higher data volume for the interval (in terms of total number of packets exchanged) is selected, and data volume in terms of packets and bytes for each interval is reported for the IP_Src, IP_Dst, Protocol tuple in [Network Info i].

Playback Info is represented as: [*Playback Event*, *Epoch Time*, *Start Time*, *Playback Progress*, *Video Length*, *Playback Quality*, *Buffer Health*, *Buffer Progress*, *Buffer Valid*]. From the perspective of video playback, a YouTube session can contain three exclusive regions: *buffering*, *playing*, and *paused*. YouTube IFrame API considers a transition from one playback region into another as an event. It also considers as an event any call to the API to collect data. The API enables the recording of an event and of detailed information about playback progress at the time the event occurs. *Epoch Time* marks the time of the most recent collection of YouTube API data in that interval. *Playback Info* records events occurred during the 100 ms interval.

Each field of *Playback Info* is defined as follows:

- **Playback Event** - This field is a binary array with four indexes for the following states: 'buffering', 'paused', 'playing', and 'collect data'. The 'collect data' event occurs every 100 ms once the video starts playing. For example, an interval with a Playback Event [1,0,0,1] indicates that playback region has transitioned into 'buffering' during the 100 ms interval and a 'collect data' event occurred.
- **Epoch Time** - This field is the UNIX epoch time in milliseconds of the most recent YouTube API event in the 100 ms interval.
- **Start Time** - This field is the UNIX epoch time in milliseconds of the beginning of the experiment.
- **Playback Progress** - This field reports the number of seconds the playback is at epoch time from the start of the video playback.
- **Video Length** - This field reports the length of the entire video asset (in seconds).
- **Playback Quality** - This field is a binary array of size 9 with indices for the following states: unlabelled, tiny (144p), small (240p), medium (360p), large (480p), hd720, hd1080, hd1440, and hd2160. The unlabeled state occurs when the video is starting up, buffering, or paused. For example, a Playback Quality [0, 1, 1, 0, 0, 0, 0, 0, 0] indicates that during the current interval, video playback experienced two quality levels - tiny and small.
- **Buffer Health** - This field is defined as the amount of buffer in seconds ahead of current video playback. It is calculated as:

$$\text{Buffer Health} = \text{Buffer Progress} \times \text{Video Length} - \text{Playback Progress}$$

- **Buffer Progress** - This field reports the fraction of video asset that has been downloaded into the buffer.
- **Buffer Valid** - This field has two possible values: True or '-1'. True represents when data is being collected from the YouTube IFrame API. '-1' indicates when data is not being collected from the YouTube IFrame API during the current interval.