Estimating WebRTC Video QoE Metrics Without Using Application Headers

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ABSTRACT

The increased use of video conferencing applications (VCAs) has made it critical to understand and support end-user quality of experience (QoE) by all stakeholders in the VCA ecosystem, especially network operators, who typically do not have direct access to client software. Existing VCA QoE estimation methods use passive measurements of application-level Real-time Transport Protocol (RTP) headers. However, a network operator does not always have access to RTP headers, particularly when VCAs use custom RTP protocols (e.g., Zoom) or due to system constraints (e.g., legacy measurement systems). Given this challenge, this paper considers can we use more standard features in the network traffic, namely the IP and UDP headers, to provide per-second estimates of key VCA QoE metrics such as frames rate and video resolution. We develop a method that uses machine learning with a combination of flow statistics (e.g., throughput) and features derived based on the mechanisms used by the VCAs to fragment video frames into packets. We evaluate our method for three prevalent VCAs running over WebRTC: Google Meet, Microsoft Teams, and Cisco Webex. Our evaluation consists of 54,696 seconds of VCA data collected from both (1), controlled in-lab network conditions, and (2) 15 real-world access networks. We show that our approach yields similar accuracy compared to the RTP-based baselines, despite using only IP/UDP data. For instance, we can estimate frame rate within 2 FPS for up to 83.05% of one-second intervals in the real-world data, which is only 1.76% lower than using the RTP headers.

CCS CONCEPTS

• **Networks** → **Network measurement**; **Network management**.

KEYWORDS

Video Conferencing, Quality of Experience, Machine Learning, Access Networks

IMC '23, October 24–26, 2023, Montreal, QC, Canada

ACM ISBN 979-8-4007-0382-9/23/10…$15.00
https://doi.org/10.1145/3618257.3624828

ACM Reference Format:
Taveesh Sharma, Tarun Mangla, Arpit Gupta, Junchen Jiang, and Nick Feamster. 2023. Estimating WebRTC Video QoE Metrics Without Using Application Headers. In *Proceedings of the 2023 ACM Internet Measurement Conference (IMC '23), October 24–26, 2023, Montreal, QC, Canada.* ACM, New York, NY, USA, 17 pages. https://doi.org/10.1145/3618257.3624828

1 INTRODUCTION

As users continue to depend on video conferencing applications (VCAs) for remote participation in work, education, healthcare, and recreation, ensuring a high quality of experience (QoE) when using VCAs is critical. Although QoE depends to some degree on the specific circumstances of end users, network operators can often play important role in mitigating QoE degradation resulting from poor local network conditions. A network operator who can observe a VCA's QoE metrics may be able to diagnose and react to QoE degradation, potentially preventing even transient congestion events from affecting user experience. Unfortunately, network operators lack direct access to application QoE, and must infer QoE from the encrypted application traffic as it traverses the network. Methods exist to infer QoE from video-on-demand applications, but these methods do not apply to inferring QoE for VCAs, which turns out to be a different problem. An important distinction et delay or loss by relying on a large playout buffer (i.e., of at least a few seconds); on the other hand, VCAs must keep a short jitter buffer (specifically, less than 100 ms) and thus are susceptible to a wide range of incidents that can disrupt or degrade network quality.

In this paper, we explore *how to enable network operators to infer objective VCA QoE metrics at a per-second time granularity from passive measurements of network traffic.* QoE is inherently subjective [22], making it challenging to infer on a large scale, even for service providers, let alone network operators who have no data from instrumentation of the client which can be useful for directly inferring user experience. To address this challenge, objective application metrics are commonly employed as a substitute for subjective QoE. The precise relationship between these application-level metrics and user QoE can be determined through user studies or data-driven methods [5] – this is complementary to the estimation of objective application metrics and is out of scope of this paper. Furthermore, although VCA performance is determined by both audio and video, past work has extensively examined audio QoE as a function of network quality of service metrics [4, 12]. Our primary focus, therefore, is to infer objective metrics (described in Section 2) that impact VCA video quality.

Recent work has proposed data-driven techniques, often leveraging machine learning, to estimate VCA QoE metrics from network-layer metrics [9, 35, 45]. However, most of these studies assume the ability to parse application-level headers, which is not always the case. Some VCAs, like Zoom, use proprietary application protocols, posing challenges for extracting information using standard network monitors [32]. In recent work, Michel et al. [34] develop a method to detect Zoom application traffic and extract encapsulated application headers. Yet, the proposed approach will not work if Zoom changes its protocol format (e.g., if it starts using a more complex encapsulation mechanism in the future). Moreover, application headers are encrypted in certain scenarios, such as when traffic is routed over a virtual private network (VPN), and it is likely that all application headers will eventually be encrypted even for regular traffic [42]. Thus, *this paper proposes methods to estimate video QoE using more standard features of the network traffic, specifically only IP/UDP headers.* A notable advantage of using IP/UDP headers is that existing network monitoring systems can readily extract such information at scale [41].

The QoE inference method we develop uses the semantics of video delivery in VCA network protocols: due to VCAs' real-time nature, each video frame is encoded and transmitted immediately. These transmission characteristics give rise to packet sizes and inter-arrival times that contain important signal about various QoE metrics, such as frame rate. By leveraging these insights, we develop both a heuristic and a machine learning-based model that estimate VCA QoE metrics at a fine time granularity. We evaluate our approach on three popular VCAs (Meet, Teams, and Webex) that use WebRTC, an open-source framework providing real-time communication capabilities to browsers and smartphones [1]. To evaluate our approach, we collect data from in-lab under diverse emulated network conditions as well as from 15 households spanning different ISPs and speed tiers over a period of two weeks. Our evaluation demonstrates that the proposed method achieves high accuracy in estimating video QoE metrics for VCAs.

We make the following contributions:

- We develop a machine learning-based method that uses features informed by mechanisms used by VCAs to fragment a frame into packets and infer VCA QoE metrics at finer time granularity using only the IP/UDP headers
- We develop an automated browser-based, VCA data collection framework and use it to evaluate our approach by collecting data under controlled in-lab network conditions as well as data from 15 households spanning a variety of ISP and speed tiers over a period of two weeks. Both the code and data from the paper has been made public [40].
- We demonstrate that using only IP/UDP headers can yield frame rate estimates within 1.50 frames of the ground truth QoE on an average. To put it in perspective, we also compare accuracy using RTP headers which is 1.33 of the ground truth QoE on average, a difference of only 0.17 frames.
- We show a prediction model trained on data from controlled lab settings transfer to real-world networks. Our results show that the model transfers with marginal drop in accuracy for two out of three VCAs. Furthermore, we characterize the network conditions under which the model have high errors and the potential reasons leading to errors.

[1]We focus on WebRTC-based VCAs as it provides mechanisms to collect ground truth QoE metrics, which are essential to evaluate the method we have developed. Our approach, however, applies to all VCAs that use Real-time Transport Protocol (RTP)

2 PROBLEM CONTEXT

We provide background on video conferencing applications, the QoE metrics, and detail the QoE inference problem.

2.1 Video Conferencing Applications

VCAs typically use Real-Time Transport Protocol (RTP) [38] for sending audio and video data and Real-Time Transport Control Protocol (RTCP) [23] for control traffic. Although VCAs can independently implement each of these protocols in the application, the WebRTC open-source real-time communication framework has become extremely prevalent, as it is supported by most modern browsers and devices (e.g., Android). We focus on WebRTC-based VCAs.

QoE metrics. We focus on inferring objective metrics pertaining to the video quality of conferencing. More specifically, we focus on the following four metrics: (1) *Video bitrate,* defined as the total number of bits received per second, with a lower bitrate indicating lower video quality.; (2) *Frame rate*, defined as the number of video frames received by the application per second. A low frame rate leads to reduced smoothness and realism of viewing experience ; (3) *Frame jitter* calculated as the standard deviation of the time gaps between consecutive frames or inter-frame delay. A high frame jitter also affects smoothness of video playback, resulting in a jerky playback. and (4) *Resolution*, the number of pixels in a video frame, with lower resolution indicating lesser details in the video.

Additional metrics can affect a VCA's QoE, including end-to-end network latency, as well as the resulting quality of the audio [17]. End-to-end network latency can be challenging to measure from a single vantage point for UDP-based traffic; previous work already estimates audio QoE for VoIP [12].

2.2 Inference Problem

Problem Statement. We take as input a sequence of packets collected from access nodes (e.g., border router), and output the desired QoE metrics at a W-second granularity. The choice of W ultimately depends on the network operator's ability to react to the inferred QoE degradation by, for example, reconfiguring the network to mitigate the inferred QoE degradation incidents. We also assume that the input consists only of RTP packets from the VCA and contains no other traffic. We can safely make this assumption because previous work has developed traffic classification methods to identify packets associated with a specific VCA session [36].

Measurement Context. We consider the case when operators use only IP and UDP headers. This scenario is motivated by several observations: First, for some VCAs that use non-standard versions of RTP (e.g., the native Zoom client [32]), network operators do not have access to RTP headers as these VCAs. Second, as has transpired with many other applications and protocols (e.g., DNS [7], TLS [10]),

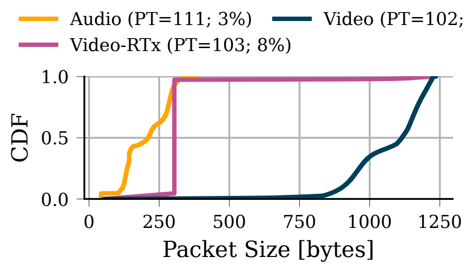


Figure 1: Packet sizes vs payload type for Teams.

we expect VCAs to encrypt the RTP headers in the future. Finally, extracting IP and UDP headers is much more efficient and scalable than extracting RTP headers; in fact, many existing network monitoring systems [41] already support extracting IP/UDP headers along with packet sizes and times.

3 METHOD

In this section, we describe our QoE estimation method that uses only IP/UDP headers. We assume access to traffic from a single VCA session and it consists of two steps. The first step involves isolating the video traffic from the audio component. Given the distinct transmission techniques (e.g., encoding, error control) used for audio and video, it becomes important to differentiate audio and video packets. Once the video traffic is identified, the second step involves using information from this traffic to infer the video QoE metrics. We first describe these two steps for our method. This is followed by a description of RTP baselines used for comparison.

3.1 Media Classification

Past work to distinguish media type relies on RTP headers [32, 36]. More specifically, a seven-bit RTP header called *payload type* can be used to identify the payload format. For example, in case of Teams, we observe three different payload types (PT): (1). PT = 111 for audio encoded using OPUS, (2) PT=102 for video encoded using H.264, and (3) PT = 103 for video retransmissions. However, with no access to RTP headers, it becomes challenging to identify the media type of an RTP packet.

To overcome this challenge, we use the insight that voice samples can be encoded in fewer bits than images. As a result, the audio packets are typically smaller than video packets. Figure 1 illustrates this phenomenon, showing the CDF of packet sizes corresponding to audio, video, and video retransmissions from 16528 seconds of Teams calls (see Section 4 for details). The actual packet media type is identified using the *RTP Payload Type* header. The audio packet sizes range between [89, 385] bytes; the video packets are significantly larger, with 99% of packets being larger than 564 bytes. Among video retransmissions, which constitute 8% of video packets, we find a significant proportion (92%) of packets with a packet length of 304. These are likely keep-alive messages for the retransmission transport stream as retransmissions are typically only sent in the case of packet losses. Because these packets do not contain any video payload, it makes sense to filter them out from the QoE inference step. The remaining video retransmission packets are significantly larger.

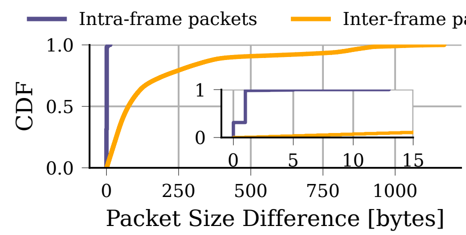


Figure 2: Intra- and inter-frame packet size difference for Teams

This characteristic allows us to use a size threshold denoted as V_{min} to identify video packets. Any packet with size greater than or equal to V_{min} is tagged as a *video* packet, while the remaining packets are not considered. The value of V_{min} can be determined by inspecting a few VCA traces collected in the lab.

3.2 QoE inference

We develop two approaches to infer QoE metrics from video traffic using only IP/UDP headers. The first approach, referred to as IP/UDP Heuristic, utilizes VCA video delivery semantics. We find that relying solely on the heuristic approach can lead to errors, particularly under high network jitter and loss. We thus propose a machine learning(ML)-based approach called IP/UDP ML that relies on a combination of network features, including both statistics on network traffic and features derived using insights from the IP/UDP Heuristic.

3.2.1 Heuristic. Because VCAs are real-time and low latency application, each video frame generated at the sender is transmitted over the network as soon as it has been encoded. From the network perspective, each frame comprises one or more RTP packets. The VCA client transmits these packets immediately, without waiting for additional frames. As a result, *a VCA session can be abstracted as a sequence of video frames, with each frame transmitted sequentially over a group of RTP packets separate from other frames.* Identifying the video frame boundaries (by identifying frame end time) and frame size can enable inference of key QoE metrics described in Section 2. Past work has relied on using RTP headers to identify frame boundaries [32]. Without access to the RTP headers, it is challenging to identify the frame boundaries.

Key Insights: To identify frame boundaries using IP/UDP headers, we use insights from the mechanisms that VCAs use to divide frames into packets. We first consider whether there are patterns in packet inter-arrival times (IAT). A frame is packetized and transmitted immediately, which leads to microbursts on the network, causing the inter-departure times to be shorter for packets within the frame as compared to packets across frames. Unfortunately, this insight is challenging to apply reliably to determine frame boundaries as packet timings can change when packets traverse along the network. Thus, the patterns in the inter-departure times may not appear in the inter-arrival time (IAT) at the receiver.

We next consider whether there are unique patterns in packet sizes. An advantage of using packet size is that it does not change during packet transmission over the network. Interestingly, we find a unique pattern in the packet sizes, i.e., packet sizes tend to resemble those within the same frame and differ from packet sizes in consecutive frames. This phenomenon occurs because VCAs typically fragment a frame into equal-sized packets. This is done because the Forward Error Correction (FEC) mechanisms used to protect against network losses are most bandwidth-efficient when packets in a frame have equal length [25, 27]. Furthermore, due to dynamic nature of the underlying video content along with variable bitrate encoding used by VCAs, consecutive frames exhibit different sizes and, consequently different packet sizes.

Figure 2 illustrates this characteristic, showing the CDF of size difference in consecutive intra-frame and inter-frame packets, for more than 360,000 frames. The true frame boundaries are identified based on the RTP timestamp header as explained in Section 3.3. For frames with more than two packets, we show only the maximum size difference across all packets. The inter-frame size difference is the absolute size difference between the first and the last packets of two consecutive frames. We find that the intra-frame packet size difference is less than two bytes for all but one packet. The inter-frame packet size difference on the other hand is at least 2 bytes for more than 99.4% of the frames.

Frame boundary estimation: Thus, we use a packet size difference threshold Δ_{size}^{max} and declare frame boundary if the size difference between consecutive packets is greater than Δ_{size}^{max}. However, it is not sufficient to compare only consecutive packets as packets can arrive out of order. Therefore, instead of comparing with only the last packet, we iteratively compare with up to N^{max} packets that arrived before this packet, beginning with the most recent packet. If the size difference of the current packet is within Δ_{size}^{max} for any of these packets, it is considered as part of the same frame as the matching packet. Otherwise, the packet is assigned as a part of new frame. The exact heuristic is described in Algorithm 1 in the Appendix.

The parameters of the heuristic, i.e., N^{max} and Δ_{size}^{max}, can be determined by inspecting few traces for a given VCA in the lab. Intuitively, a large value of N^{max} can account for all out-of-order packet arrivals. However, it also increases the probability of incorrectly combining a packet from a new frame to an earlier frame with a similar size. Thus, the value of N^{max} should be set carefully. We analyze the sensitivity of the heuristic to different values of N^{max} in our evaluation.

QoE estimation from frames: Once the frame boundaries have been identified, for a single session S, we obtain a sequence of frames along with their sizes. We use this information to estimate the key QoE metrics over a window W of duration w seconds in the following manner:

- **Video bitrate**: It is simply the time average of the total bits across all frames transmitted in the window W.
- **Frame rate**: It is simply the number of frames transferred per second in the window W. More specifically, Frame rate = $\frac{\sum_{i=1}^{N} I(ET_i \in W)}{w}$. Here, indicator function I equals one if the frame end time is within the window, and zero otherwise.
- **Frame jitter**: It is calculated as the standard deviation of difference in end times (ET_i - ET_{i-1}) of consecutive frames received over the window W.

We do not estimate frame resolution using this method as there is no direct signal in the frame reflecting its resolution. Intuitively, one can design a machine learning-based method that uses frame sizes and FPS from the heuristic to predict video resolution. This, however, is similar in principle to the machine learning-based method described in Section 3.2.2; hence, we skip implementing the approach for simplicity.

3.2.2 Machine Learning Approach. **Why use machine learning?**: The heuristic described in Section 3.2.1 relies on assumptions that can break under certain conditions. For instance, under high latency jitter or packet loss, packets can arrive out of order leading to incorrect estimation of frame boundaries. Although we add parameters (e.g., use a packet lookback $N^{max} > 1$) that alleviate the errors to some extent, it still does not completely solve the problem. More importantly, there are other, complimentary, signals in the network data that can inform QoE estimation. For instance, given the real-time nature of the VCAs, throughput is a potential indicator of few QoE metrics such as video bitrate. Including multiple such signals into a heuristic can quickly make it complicated. Therefore, we consider a data-driven approach that considers multiple features derived from the network data along with supervised machine learning models. We now describe our approach.

Input features: We use a common set of features to predict all QoE metrics. The features considered can be divided into two categories:

- **VCA semantics-based**: These include two features that are informed by how VCAs fragment frame into packets as described in Section 3.2.1. The first feature is the number of unique packet sizes observed in the prediction window W. The second feature is the number of microbursts of packets in the prediction window W. A microburst is defined as a sequence of packets with the consecutive inter-arrival times within a threshold θ_{IAT}. Therefore, the microburst count is simply the number of consecutive packets with inter-arrival time $\geq \theta_{IAT}$. Intuitively, these features can help inform the frame boundaries and consequently the key video QoE metrics.
- **Flow-level statistics**: We also derive a set of key statistics from the IP/UDP headers of video packets. These include number of bytes and packets per second as well as five statistics on packet sizes and inter-arrival times namely mean, standard deviation, median, minimum and maximum. Intuitively, given the real-time nature of VCAs, any transient degradation in the VCA QoE metrics would also be evident in one or more of these statistics.

In total, we compute 14 features for each prediction window W as summarized in Table 1.

3.3 RTP Baselines

To benchmark the accuracy of our approach using IP/UDP headers, we also consider two RTP-based approaches as baselines. The first approach is a heuristic approach, called RTP Heuristic, and the other is a machine learning-based approach called RTP ML. We now describe both of these approaches.

RTP Heuristic: This is similar to the approach used by Miche; et al. to estimate QoE metrics for Zoom [34] and is based on the same insight as the IP/UDP Heuristic approach, i.e., a VCA session can be modeled as a sequence of frames. To identify frame boundaries, it uses the *RTP timestamp* field from the packet headers. The *RTP timestamp* is used to determine the correct order for media playback, as well as to synchronize audio and video streams. Packets belonging to the same frame receive the same *RTP Timestamp*, and thus the

Category	Features
Flow-level statstics	Bytes per second, packets per second, packet size (5) and inter-arrival statistics (5)
IP/UDP features based on VCA semantics	# unique packet sizes, # microbursts
RTP Headers	# unique RTP timestamps (4), marker bit sum (1), out-of-order sequence (1), RTP lag (5)

Table 1: Summary of features extracted from traffic. Numbers in parenthesisparantheses reflect the count of features. The IP/UDP ML approach uses the first two categories of features, while the RTP ML approach uses the first and third category of features.

field can be used to identify frame boundaries. To detect the end of frames, the approach also uses the *Marker bit* in the RTP header. This bit is set only for the last packet of each frame and is used to detect the end of frames.

Using this approach, we can identify the sequence of frames in the prediction window W, along with frame completion time and frame size. We then use similar method as described in Section 3.2.1 to estimate frame rate, frame jitter and bitrate.

RTP ML: This is similar to the IP/UDP ML approach and uses machine learning-based methods to estimate QoE metrics. The input features, however, are derived from RTP headers. We consider the following set of RTP-based features:

- **RTP timestamps:** We calculate the number of unique RTP timestamps over each stream individually as well as their intersection and union.
- **Marker bit sum:** It is the sum of marker bit for all packets in the prediction window. We calculate this feature separately for video and retransmission streams.
- **Number of out-of-order video sequence numbers:** We calculate the total number of discontinuities in video packet RTP sequence numbers over the prediction window. It is used as a signal for packet re-ordering and loss.
- **RTP Lag:** It captures the delays in frame transmission. We assume that the first frame had zero delay. For each frame i, we calculate the transmission delay as the difference between its reception time t_i and transmission time, which is calculated as $t_0 + \frac{RTP_i - RTP_0}{SF}$. Here, SF is the sampling frequency for generating RTP timestamps and is typically 90,000 for most video codecs [25]. We then calculate the five statistics across frame transmission delays.

In addition, we also use the flow-level statistics as summarized in Table 1. This is done for similar reasons as described for the IP/UDP ML approach.

4 EXPERIMENT SETUP AND DATASETS

This section describes our experimentation framework and the different datasets we use to evaluate our methodology.

We consider WebRTC-based VCAs for evaluation as WebRTC is a popular framework used by most VCAs for their browser version. Moreover, it is possible to obtain ground truth QoE metrics for WebRTC-based VCAs using the `webrtc-internals` API provided by Google Chrome [3]. To collect data for evaluation, we build an automated browser-based framework that initiates calls for a given VCA over a browser. The framework uses PyAutoGUI, a UI automation framework, for starting and ending the calls. We collect data three popular VCAs, namely Meet, Teams, and Webex. The framework, however, is extensible to other VCAs.

We conduct 2-person calls each lasting for a variable duration. For consistency, we use a virtual web camera at one of the endpoints streaming a predefined short video on loop and log the QoE metrics on the other endpoint. At the end of the call, we collect both network traces and WebRTC logs.

4.1 Matching ground truth with estimates.

We compare our QoE estimates with per-second metrics reported by `webrtc-internals`. We match the two datasets using the timestamp fields in the two datasets. The *webrtc-internals* reports only the start and end times of data collection. We assume that the reported per-second metrics are collected at one-second interval; this matching approach may not be perfect in certain cases, such as when WebRTC logs contain time intervals that are slightly out of phase. To address this as much as possible, during our analysis, we filter out logs where we observe fewer per-second logs compared to the duration of the call.

4.2 Network Condtions

To evaluate under diverse network conditions, we collect two kinds of data: (1). in-lab data under emulated network conditions, and (2). data from 15 households under real-world network conditions.

In-lab Data The data is collected by conducting calls between two machines in the lab under emulated network conditions. We emulate dynamic network conditions using the `tcp-info` stats dataset from the Measurement Lab's Network Diagnostic Test (NDT), a public dataset containing speed tests taken by real users across the world [2]. The test measures TCP throughput by flooding the link for ten seconds. We use the samples of instantaneous throughput and RTT, called `tcp-info` stats, collected multiple times during the test [1]. More specifically, we emulate the same sequence of RTT and packet loss values as observed in a single test, while the throughput values are sampled from a normal distribution with the same mean and variance as the test throughput. We did not use the throughput samples directly as they include throughput observed during the TCP slow-start period. Each throughput, delay, and loss value is emulated for a period of 1 second. We only use traces with average speeds below 10 Mbps to create challenging network conditions. We collect around 11k seconds, 15k seconds, and 13k seconds of Meet, Teams, and Webex data, respectively. As expected, we find differences in ground truth QoE metrics across the VCAs despite the presence of similar network conditions. For instance, the median bitrate is 500 kbps for Webex, whereas it is 1700 kbps for Teams (see Figure A.1 in Appendix for other metrics). These differences can be attributed to design variations within the VCAs. Conducting evaluation across multiple VCAs can help us understand the generalizability of our methodology.

Real-world Data. We note that the in-lab data is not a perfect emulation of the real-world networks; therefore, we complement our data with real-world VCA data. For this purpose, we deploy Raspberry Pi (RPi) devices in 15 households, directly connected to the home router. These households are recruited with the help from community organizations and are located in a major city, spanning different neighborhoods, ISPs, and speed tiers [29, 39]. Although our sample size is limited, it serves as an additional independent data source, capturing real-world network conditions, which allows us to thoroughly test our methods.

The RPi collects VCA data by initiating a 15-25s call every 30 minutes to an end point located inside a cloud network. The VCA is selected randomly from the three VCAs. The cloud endpoint and the RPi both join the VCA call as two different participants. During the call, the video on the RPi is kept off while the cloud-network end point streams a predefined video over a virtual camera interface, same as in the lab experiments. We do not stream video on the RPi as it increases the CPU utilization, leading to degradation in call quality due to non-network reasons. For each call, we log the ground truth QoE metrics and the network traffic on the RPi and export the data to a centralized server at the end of the call.

The data collection spanned over a period of two weeks and includes 320 Meet calls, 178 Teams calls, and 417 Webex calls. Compared to the in-lab data, the average QoE metrics exhibit higher values (see Figure A.2 in Appendix for the distribution). This improvement is expected as the download speeds of access networks, likely to be the bottleneck in this case, have significantly improved. We also, however, observe a small fraction of calls with low QoE, indicating the presence of variability in the real-world network conditions.

4.3 Parameter Setting and Model Training

The IP/UDP Heuristic uses two parameters, Δ_{size}^{max} and N^{max}, that are VCA-specific. We set these parameters by sampling a few sessions for each VCA. We use a value of 2 bytes for Δ_{size}^{max} across all VCAs. The value of N^{max} is set to 3, 2, and 1 for Meet, Teams, and Webex, respectively. For the ML methods, we use random forests as it was the most accurate among the classical supervised machine learning models. The accuracy numbers for these methods are reported over a 5-fold cross validation.

For the ML methodology, we experiment with several classical supervised ML models, specifically Support Vector Machines (SVMs), decision trees, and random forests. However, in this paper, we present the results obtained using only random forests, as they consistently yield the highest accuracy. This finding aligns with prior research within the field that has leveraged ML-based techniques for network data analysis [9, 14, 15, 31]. In addition, the accuracy numbers for ML-based techniques are reported after 5-fold cross-validation.

5 EVALUATION

Our evaluation analyzes the accuracy of IP/UDP methods, particularly in comparison to the RTP baselines, using both in-lab and real-world datasets. Furthermore, we examine the potential sources of errors as well as identify the most important features for ML methods. Later, we analyze the transferability of ML models, characterize the network conditions where the models err, and quantify the impact of prediction window on model accuracy.

Actual	Predicted		Total
	Non-Video	Video	
Non-video	98.3%	1.7%	67,830
Video	0%	100%	360,481

Table 2: Media classification accuracy for Meet

5.1 In-lab Data Results

We describe the accuracy of our methods in classifying media and estimating each QoE metrics for in-lab data.

5.1.1 Media Classification Accuracy. The identification of video packets is a common step for both the IP/UDP methods. The ground truth is obtained by inspecting the `Payload Type` RTP Header. Table 2 shows the normalized confusion matrix for video packet identification for Meet. The accuracy of identifying video packets is generally high. However, a small fraction of non-video packets get misclassified as video. Upon closer inspection, we find that these misclassified packets are server hello messages over DTLSv1.2 and key exchanges in the beginning of the call.

Impact of misclassification on QoE estimation. For IP/UDP Heuristic, these additional packets can result in false frame boundaries, leading to overestimation of number of frames. On the other hand, the IP/UDP ML method may be more resilient to minor errors in video traffic classification as it relies on multiple signals in the network traffic.

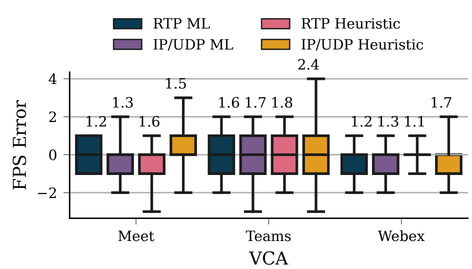


Figure 3: Frame rate errors. The whiskers represent the 10^{th} and 90^{th} percentile values. The numbers represent the MAE.

5.1.2 Frame Rate. Figure 3 shows the distribution of error in frame rate along with the Mean Absolute Error (MAE) values across VCAs. We observe a consistent trend in MAE values across all VCAs: RTP ML < IP/UDP ML < RTP Heuristic < IP/UDP Heuristic. However, we observe a deviation from this trend in Webex where MAE of RTP Heuristic is lower than that of both RTP ML and IP/UDP ML approaches and in Meet where MAE of IP/UDP Heuristic is lower than that of RTP Heuristic. Moreover, the MAE remains within 2 FPS margin in all cases, except for IP/UDP Heuristic over Teams.

In general, both heuristics tend to have higher errors compared to the ML-based methods. One potential reason for this could be that the WebRTC frame rate is reported after accounting for additional application-level delays such as jitter buffer delay which are not observable directly from the network traffic. The ML-based methods trained on application-level ground truth can potentially calibrate their prediction to account for such mismatch while this is simply not possible for the two heuristics.

Interestingly, the errors for the IP/UDP ML method have similar distribution as RTP ML. *This indicates that IP/UDP headers can estimate frame rate with comparable accuracy to RTP headers.* In contrast, the IP/UDP Heuristic has the highest errors. This is surprising as we expect IP/UDP Heuristic to have similar accuracy as the RTP Heuristic. We now examine the causes of error for the IP/UDP Heuristic approach.

Why does the IP/UDP Heuristic exhibit higher errors? The IP/UDP Heuristic relies on the observation that inter-frame packet size difference is larger than intra-frame packet-size difference. However, this is not true for few cases:

Case 1. If two consecutive frames are similar in size, it will end up combining those two frames or frame coalesces.

Case 2. If the packets within a frame have size difference greater than Δ^{max}_{size}, they will be split into multiple frames. We observe this mostly for Meet where a fraction of frames contain packets with large intra-frame packet-size difference.

Case 3. If packets arrive out-of-order, the frames will get interleaved. As a result, the heuristic will end up creating false frame boundaries and overestimate the frame rate.

We analyze the frequency of each type of error in our data as shown in Figure 4. For Meet, we observe a greater number of splits for about 0.72 frames in one prediction window on an average, leading to overestimation (see Figure 3). We detect these splits by calculating the number of frames where the intra-frame packet size is greater than Δ^{max}_{size}. In Figure 4, we also see that a higher percentage of erroneous coalesces leads to underestimation of FPS in Webex. We calculate these by estimating the number of frames to which more than one RTP timestamps were assigned by IP/UDP Heuristic in the prediction window.

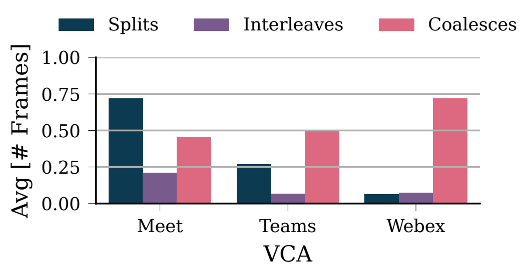


Figure 4: Different types of errors in the inter- and intra-frame packet size difference assumption

Feature importance for IP/UDP ML method. Figure 5 shows the top-5 features for frame rate prediction in the case of Teams. We observe a high feature importance for the *# unique sizes* feature. We also observe a significant importance of this feature for Meet and Webex (see Figure A.4 in Appendix). The prevalence of *# unique sizes*

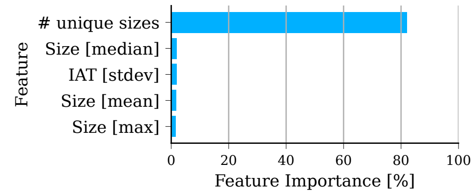


Figure 5: Top-5 feature importance scores for IP/UDP ML frame rate predictions for Teams

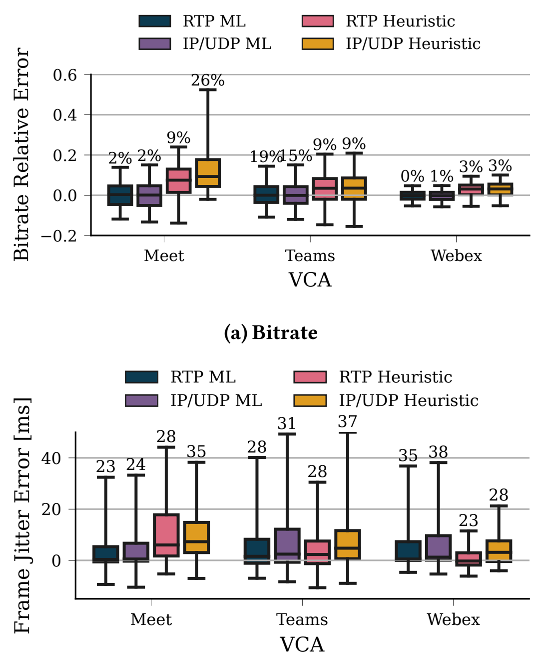


Figure 6: Distribution of errors across the VCAs. The whiskers represent 10^{th} and 90^{th} percentile values. The numbers represent the MRAE for bitrate and MAE for frame jitter.

among the top-5 features of all VCAs suggests a strong correlation between frame rate and unique packet sizes, enabling accurate frame prediction even without utilizing the RTP headers.

Notably, the other semantic-based feature, *# microbursts*, does not appear among the top-5 features. This suggests that there is significant distortion of inter-packet times along the network path. Furthermore, an ML approach, like IP/UDP ML, can take advantage of other signals in the network, which is absent in the IP/UDP Heuristic. For example, the most important feature is *IAT [min]* for Meet and *# bytes* for Webex.

5.1.3 Bitrate. We calculate the relative bitrate error, defined as the ratio of bitrate error and the ground truth bitrate. Using relative values facilitate comparison of errors across VCAs, especially because the ground truth bitrate distributions differ significantly across VCAs. Figure 6a shows the box plot of relative bitrate error distribution across the VCAs. The numbers displayed on the whiskers

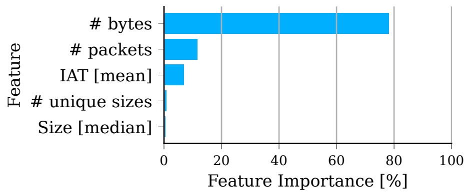


Figure 7: Top-5 features along with feature importance scores for bitrate estimation using the IP/UDP ML method for Webex

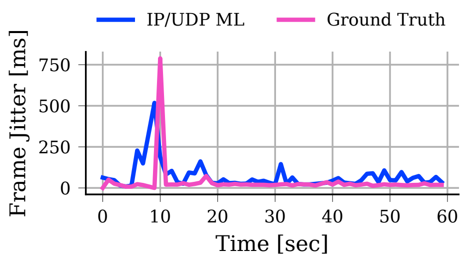


Figure 8: A time series for frame jitter IP/UDP ML predictions over a single Meet trace

represent the mean relative absolute error (MRAE). The error distribution and the MRAE values exhibit similar values for both IP/UDP ML and RTP ML methods across all three VCAs. For example, in the case of Meet, the IP/UDP ML predictions are within 25% of ground truth bitrate in 87% of cases, while in Teams, it is 89% and in Webex, it is 95%. Comparatively, in RTP ML method, these percentages are 89%, 91%, and 95% for Meet, Teams, and Webex, respectively.

We observe higher errors for both heuristics in comparison to the ML methods, except in the case of Teams. Moreover, the errors are systemic with median relative bitrate error consistently exceeding zero across all VCAs for both heuristics. This is because neither of these heuristics considers any application-layer overheads, such as due to encoding metadata. It should be noted that we do take into account the overhead due to fixed portion of the RTP headers, i.e., 12 bytes. However, incorporating encoding overheads remains challenging even with RTP headers, as these parts of the traffic are encrypted. The ML methods, on the other hand, can address these systemic errors by training on video bitrate values observed at the application level.

Feature importance for IP/UDP ML method. Figure 7 shows the top-5 important features for the IP/UDP ML method in the case of Webex. As expected, the feature *# bytes* has the highest importance. In fact, that is the case across all three VCAs. Most of the other important features also relate to data volumes, such as *Size [mean]* and *# packets*. Interestingly, we do not observe any semantics-based features among the top-5 features, except for *# unique sizes*, which appears as the fourth most important feature for Webex. This is because video bitrate is inherently correlated with observed throughput. In fact, the top-5 features for the RTP ML method are also found to be derived from flow statistics (see Figure A.7 in Appendix).

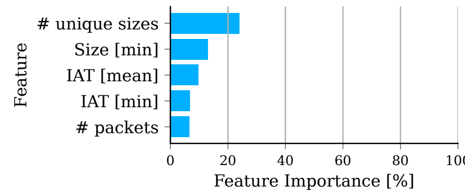


Figure 9: Top-5 feature importance scores for IP/UDP ML resolution predictions for Webex

5.1.4 Frame Jitter. Figure 6b shows the boxplot of the errors in frame jitter predictions for the three VCAs. It is evident that all methods, including the RTP-based approaches, tend to overestimate frame jitter in most cases. Furthermore, we find that the MAE values are unusually high for this metric. The average ground truth frame jitter observed across all three VCAs falls within the range of 27-33 ms, which is comparable to the MAE values obtained from all methods. Upon further examination, we discover that the WebRTC ground-truth statistic reports the jitter over decoded frames, encompassing additional application delays such as jitter buffer and decoding delays. The jitter buffer introduces variable delay to ensure smooth video playback, while decoding delays can vary based on the client's computational resources. Capturing these variable application-level delays can be challenging using only the network data.

Figure 8 illustrates this phenomenon with the frame jitter values reported by the IP/UDP ML and WebRTC for an example Meet call. The IP/UDP ML method reports several spikes in frame jitter throughout the call. While most of the smaller spikes seem to be smoothed out in the WebRTC data, there is a significant spike around t=10s that appears in both cases. Additionally, the IP/UDP ML method estimates the spike prior to t=10s, indicating jitter in frame arrival around that time. The application jitter buffer might have attempted to mitigate this frame jitter by emitting frames at constant rate until it is emptied, resulting in a larger spike later.

From the perspective of a network operator, it is more important to predict and respond to network-level frame jitter. Ensuring a smooth frame arrival will automatically lead to low frame jitter. In future work, we plan to modify our experiment methods to collect ground truth frame jitter calculated before the frame is enqueued to the jitter buffer. This will allow us to more accurately assess the error of our method by providing a reliable basis for comparison.

Method	Accuracy		
	Meet	Teams	Webex
IP/UDP ML	97.74%	87.22%	99.30%
RTP ML	97.87%	87.78%	99.31%

Table 3: Resolution estimation accuracy across VCAs

5.1.5 Resolution. We use frame height as the measure for resolution. Within our dataset, we observe 3 distinct frame height values for Meet: 180, 270, and 360; 11 distinct values for Teams ranging from 90 to 720; and only 2 distinct values for Webex: 180 and 360. For Meet and Webex, we apply classification on per-value basis. For Teams, we bin the frame height into three classes: *low* ($\leq$ 240), *medium* ((240, 480]), and *high* (> 480). Table 3 shows the overall resolution

Actual	Predicted			Total
	Low	Medium	High	
Low	96.41%	1.65%	1.95%	5038
Medium	8.08%	45.40%	46.52%	1782
High	1.20%	7.85%	90.95%	7588

Table 4: The normalized confusion matrix for resolution predictions by IP/UDP ML model for Teams.

accuracies across all VCAs. In all cases, the accuracy is comparable to that of RTP ML method.

Table 4 shows the confusion matrix for Teams using the IP/UDP ML method. It is evident that the IP/UDP ML method accurately predicts the *low* and *high* resolution classes. However, it misclassifies 46.52% of *medium* resolution intervals as *high* resolution. This discrepancy could be attributed to either class imbalance in one or more of the 5-fold cross validation splits or the inherent difficulty in distinguishing between the *medium* and *high* resolution classes. It should be noted that within the *medium* resolution bin, 70% of the intervals have a frame height of 404, which is close to the threshold of 480 used to differentiate *medium* and *high* resolution classes.

Feature importance. For IP/UDP ML method, packet size statistics consistently appear in the top-5 features for all VCAs. In fact, for Meet and Teams, 3 out of top-5 features are related to packet sizes, suggesting strong correlation between frame resolution and packet sizes. For Webex (see Figure 9), the most important feature is *# unique sizes*, indicating a correlation between frame rate and frame resolution. We find similar patterns in feature importance plots for the RTP ML method (see Figure A.9 in Appendix). The only exception is Webex, where the *# unique sizes* feature is replaced by $uniqueRTP_{vid}TS$ and $Marker_{vid}$ *bit sum* features. This finding reaffirms that packet size difference is valuable for identifying frame boundaries.

5.2 Real-world data

This section describes the results over the data collected from 15 access networks. We do observe some differences between the real-world dataset. Teams and Webex use a different `payload type` compared to the in-lab data. For Teams, we observe a `payload type` of 100 for video, 101 for video retransmission, while for Webex, the `payload type` for video is 100, with no retransmissions as in the lab data. We adjust the media classification approach for the RTP methods accordingly, while the remaining methodology is same as in-lab.

5.2.1 Frame Rate. Figure 10a shows the boxplot of frame rate estimation errors. The overall accuracy is high for the IP/UDP ML method and is comparable to the RTP ML method, a difference of 0.1 FPS across all VCAs. Interestingly, the RTP Heuristic has the highest accuracy among all methods. We believe it could be due to the fact that network conditions are more stable in the real-world data, thus reducing any errors in RTP Heuristic due to any application-level delays such as jitter buffer delay.

The IP/UDP Heuristic, on the other hand, has the highest errors among all methods. While, the MAE difference between IP/UDP Heuristic and RTP Heuristic is only 0.5 FPS and 0.7 FPS for Teams and Webex, it is 2.3 FPS for Meet. Upon further inspection, we find that the high errors for Meet are because of higher fraction of frames in the real-world data where the intra-frame packet size difference is greater than the Δ_{size}^{max}, the threshold used to determine frame boundaries. More specifically, in the lab data, the intra-frame size difference exceeded Δ_{size}^{max} for only 4.26% frames, while this number is 14.48% in the real-world data. This also explains consistent overestimation for Meet. Note that using a higher value for Δ_{size}^{max} will not help as it will lead to underestimation due to combining of frames with similar size. The discrepancy in Meet could be a codec-specific issue, Meet uses VP8 or VP9 while both Teams and Webex use H.264, leading to fragmentation of frames into unequal-sized packets. We will examine this further in our future work.

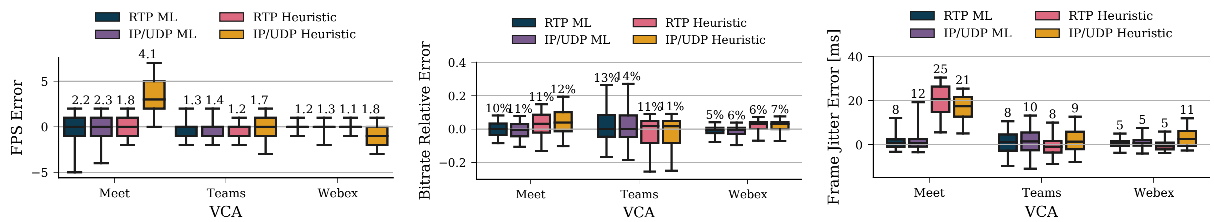
We also notice this anomaly in the feature importance analysis for IP/UDP ML. While *# unique sizes* is among the top-5 features for Teams and Webex, it is not the case for Meet. Instead, this is replaced by the IAT statistics, indicating that packet arrival patterns are better signals for detecting frame boundaries. This finding confirms that *# unique sizes* is not as strongly correlated with frame rate for Meet in the real-world data. This also shows the resiliency of ML models as they can rely on multiple features together more effectively.

5.2.2 Bitrate. Figure 10b shows the boxplot of relative error distribution with overall MRAE values mentioned over the top whisker. The MRAE values in the real-world data are smaller compared to the in-lab data across all methods. For example, IP/UDP ML method can estimate bitrate within 25% of ground truth in 92.17% of the intervals for Meet, 82.43% for Teams, and 95.14% for Webex. This is likely because the bitrate values are more stable, making them easier to predict. The feature importance trends for bitrate were found to be similar as in-lab data for each VCA. The most important features for both RTP ML and IP/UDP ML are again derived from flow statistic and correspond to data volume such as *# bytes* and *# packets*.

5.2.3 Frame Jitter. We observe that the overall frame jitter errors are lower in the real-world data compared to the in-lab data for most methods (see Figure 10c and Figure 6b). For example, when analyzing IP/UDP ML MAE value for Meet, the MAE is 9.3 ms in real-world data, whereas it is 22.6 ms for in-lab data. This difference is likely because the network conditions tend to be more stable in the real-world dataset. This leads to lower network-level frame jitter, reducing the smoothening effect of the application-level delay jitter buffer. Thus, the differences between the predicted frame jitter (only network-data) and the WebRTC frame jitter (includes effect of application delay jitter buffer) will be smaller, leading to reduced overall errors. The remaining trends are similar as the in-lab data.

5.2.4 Resolution. The real-world dataset for Meet contains two additional frame height values: 540 and 720. This is likely because of greater throughput availability and explains the greater overall bitrate values for Meet. For Teams, the same set of resolution values were observed as in-lab data. For Webex, we only observe a single resolution, and thus skip its accuracy computation.

The accuracy for resolution classification using IP/UDP ML is 96.26% and 86.82% for Meet and Teams, respectively. This is comparable to the RTP ML accuracy – 96.75% for Meet and 87.11% for Teams, respectively. As in the lab data, in this case as well IP/UDP ML model can distinguish extreme resolution values (see Table A.3 for Teams) with high accuracy, while the accuracy is low for *medium* resolution intervals.



(a) Frame rate **(b) Bitrate** **(c) Frame jitter**

Figure 10: Distribution of errors across the VCAs for the real-world dataset. The whiskers represent the 10^{th} and 90^{th} percentile values. The numbers above the top whisker represent the MAE values for frame rate and frame jitter and MRAE for bitrate.

Method	VCA		
	Meet	Teams	Webex
IP/UDP ML	12.41	2.07	1.56
RTP ML	3.11	2.51	1.51

Table 5: Frame rate MAE results after using lab-trained models to predict real-world MAE

5.3 Model Transferability

We examine the transferability of ML models by testing the in-lab trained ML models with the real-world data. Table 5 shows the overall MAE values for frame rate estimation. When considering the IP/UDP ML approach, there is a slight increase in MAE for both Teams and Webex, specifically 0.7 FPS and 0.3 FPS, respectively, compared to using models trained on real-world data. However, for Meet, the MAE significantly increases by 10 FPS. Upon further inspection, we find that *IAT [min]* is the most important feature for the in-lab-trained IP/UDP ML model in this case. Considering the disparity in bitrates between real-world and lab data for Meet, it is likely that the IAT distribution differs as well, consequently leading to errors in frame rate prediction. Interestingly, the decline in performance for Meet using the RTP ML method is not as pronounced as observed in the IP/UDP ML method. This disparity can be attributed to the higher importance of the number of unique RTP timestamps as a feature which in some sense is a direct indicator of frame rate compared to IAT.

The trend persists for video bitrate and resolution with a significant drop in accuracy for Meet, but only a slight decrease for Teams and Webex (see Tables A.4 and A.5 in Appendix). The non-transferability for Meet can again be attributed to the presence of a distinct distribution that was not previously encountered, i.e, calls with high bitrate and high resolution. This discrepancy suggests that the model lacks the ability to effectively extrapolate to unseen distributions.

5.4 Effect of Network Conditions

We next characterize the network conditions under which the models yield high errors. To do so, we collect data under synthetic network conditions by varying one of the following five network parameters: throughput (1500 kbps), throughput jitter (0 kbps), latency (50 ms), latency jitter (0 ms), and packet loss (0%). The numbers in parantheses represent the default values. For example, to analyze the impact of loss, other parameters are set to default values and loss is varied

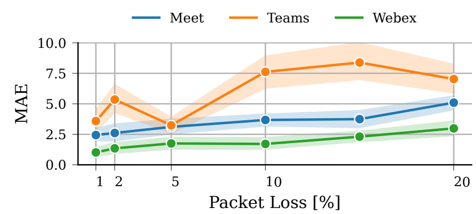


Figure 11: IP/UDP ML MAE for frame rate with varying network loss. The bands represent 95% confidence intervals

from 0% to 20% following a Bernoulli loss model. Each combination of network conditions is repeated for four calls. For training ML models, we use 50% of data, sampling uniformly randomly from each combination of network condition. The remaining 50% data is used for testing.

Figure 11 shows the accuracy under varying loss for the IP/UDP ML method. Barring few exceptions, we observe an increasing trend in errors as network loss increases. On further inspection, we found that losses lead to retransmissions for video packets, leading to packet reordering. It is not possible to determine the correct order of the packets using only IP/UDP headers which causes higher errors. We find that the errors are even higher for the IP/UDP Heuristic as it relies only on packet sizes, and is more severely impacted by packet reordering. We also observe similar behavior under high latency or throughput jitter likely because both also lead to packet reordering. However, this occurs at very high values of jitter, indicating some robustness to minor jitters in the network. The errors do not change significantly with varying mean throughput or mean latency.

5.5 Effect of Prediction Window Size

We analyze the impact of prediction window size on QoE estimation accuracy. Figure 12 shows the IP/UDP ML MAE values for frame rate under varying prediction window. The errors decrease as the prediction window size increases. This can be attributed to two reasons: (1). larger window sizes reduce the impact of sub-second-level window misalignment between packet traces and WebRTC logs, and (2). the frame rate values become more stable as they are smoothed out over larger window, making the prediction task easier. We observe similar patterns across other methods and metrics.

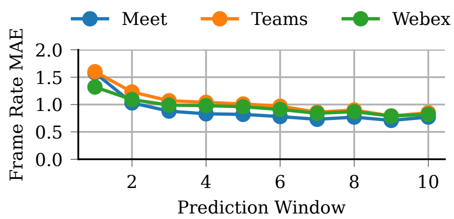


Figure 12: Variation of IP/UDP ML MAE with prediction window size for frame rate predictions for in-lab traces

6 RELATED WORK

QoE Inference for Video Streaming. Past research has made substantial progress in inferring QoE for on-demand video streaming. One set of approaches propose heuristics that model a video session relying on the properties of the underlying streaming protocol [13, 30, 37]. The second set of approaches propose using supervised machine learning and use features derived from network data to estimate QoE metrics [4, 8, 26, 33]. Inferring QoE for video conferencing is a fairly distinct problem from video streaming due to the differences in the nature of two applications, consequently leading to differences in the underlying application and transport protocols, and the metrics that determine user QoE. This paper tackles the problem of QoE inference for VCAs and proposes both heuristic- and ML-based approaches.

VCA measurement studies. Early VCA measurement studies focused on understanding the design and network performance of Skype, one of the first and the most popular VCA of the time [6, 19, 21]. More recent studies have revisited similar questions for modern VCAs [11, 20, 24, 28, 36]. Most of these studies rely on controlled experiments and assume access to end-hosts to collect VCA performance data. For instance, He et al. [20] identify the functional differences (e.g., congestion control mechanisms) among modern VCAs using controlled measurements. Our work considers a different question, i.e., how to infer video QoE metrics without access to end-hosts? Answering this question can enable network operators to understand VCA performance for a wide-variety of application and network contexts and appropriately manage their networks.

VCA QoE inference. Past work has proposed data-driven techniques, based on supervised machine learning, to estimate QoE for *Voice over IP* [4, 12]. More recent works propose similar techniques but focus on *video* performance over VCAs. These works differ, however, in the set of inferred QoE metrics as well as the network features used for inference. For instance, Garcia et al. infer metrics assuming access to an unimpaired reference video[18]. Similarly, Yan et al.[44] use WiFi-specific features to predict "good versus bad" QoE over the entire VCA session. We focus on inferring no-reference, *objective* VCA QoE metrics using measurements of passive network traffic. Works by Nikravesh et al.[35] and Carofigilo et al. [9] are similar in spirit in that regard. However, both of these works assume access to RTP headers which may not be practical in many cases such as with custom RTP protocols (e.g., Zoom), encrypted application-layer headers (e.g., VPN), or legacy monitoring systems. Recent work by Oliver et al. [32] uses entropy-based header analysis to infer Zoom's RTP encapsulation mechanisms. However, the approach may not work if VCAs use complex encapsulation mechanisms or encrypt application-layer headers altogether. Morevoer, it requires network monitoring systems that can process arbitrary portions of the traffic. This may not be feasible for several network operators due to practical considerations. This paper considers whether more standard features of the network traffic, i.e., IP/UDP headers, can be used to infer the VCA QoE metrics.

7 LIMITATIONS AND FUTURE WORK

Generalizability to other VCAs. Our paper's evaluation is focused on WebRTC-based VCAs, although our methodology can be applied to any RTP-based VCA. The reason to focus on WebRTC is the lack of methods to obtain application-level QoE metrics for native VCA clients. Additionally, we do not include the WebRTC version of Zoom, one of the most popular VCAs, as its implementation uses the `datachannel` API meant for non-audiovisual communication. As a result, the video QoE metrics are no longer available for Zoom through the `webrtc-internals` API. Past work has considered other metrics to obtain QoE metrics from the applications. Michel et al. [34] used a custom Zoom client, but this approach will not work for the native client of other VCAs. Another method to obtain application-level logs is through screen capture of annotated video [16, 43], but this method is resource intensive. Future work will explore generalizable and lightweight methods to obtain application-level QoE logs for native VCA clients and assess the accuracy of proposed QoE estimation methods for these clients.

Cost of ML models. Using supervised ML models can be costly due to the expense of acquiring labeled data for training. We present one solution to gather labeled data, i.e., through automated data collection frameworks, deployed either in-lab or across multiple network vantage points. The framework is easily extensible to other WebRTC-based VCAs. Another solution to explore in future would be whether direct or calibrated estimations from non-machine learning methods like IP/UDP Heuristic or RTP Heuristic can be used as alternatives to labeled data.

Impact of application modes. We only evaluate our methodology in a two-person call scenario. However, modern VCAs offer various other application modes, such as disabling video, multi-party conferencing, and screen sharing. Determining whether user video is disabled seems possible by analyzing UDP packet size distribution, but the other two modes pose challenges in QoE estimation, especially using only IP/UDP headers. In multi-party scenarios, multiple video streams may be transmitted over the same UDP flow. This may require an additional step in our methods to estimate the number of participants before estimating QoE. Similarly, when screen sharing is enabled, adjustments to the media classification steps will be required. These adjustments may be based on insights from differences in encoding of video and screen sharing data. Additionally, a machine learning-based QoE inference approach such as IP/UDP ML, when trained with appropriate data, could accurately estimate QoE metrics even across different application modes. Further research will explore this question and quantify the impact of application modes on the accuracy of our methods.

System considerations. In theory, our approach relies on lightweight features from the IP/UDP headers of network traffic. However, we have not tested the scalability of our methods on a network-wide level, particularly when it comes to real-time QoE estimation. Additional optimization might be required in the implementation of our methods such as using efficient data structures or implementation of streaming versions of the methods. In future work, we plan to implement these approaches within a real-world network, such as campus network, to assess the scalability of our approach.

8 CONCLUSION

We have developed and evaluated two methods to infer QoE for WebRTC-based VCAs at per-second granularity. Evaluation of our method under diverse network conditions demonstrates the model's ability to estimate QoE metrics with high accuracy, even if the methods relies on only IP/UDP headers. This approach represents a significant advance over previous work, which uses information in the RTP headers. Future work will explore the generalizability of our methods to a broader set of clients (e.g., device, operating systems, native clients) and application modes (e.g., multi-party calls).

ACKNOWLEDGEMENTS

We would like to thank our shepherd, Gianni Antichi and the anonymous reviewers for their valuable feedback. We also thank Guilherme Martins for helping with the real-world data collection and Irene Pattarachanyakul for her efforts towards earlier version of this research. The work was supported by National Science Foundation (NSF) awards CNS-2124393, CNS-2223610, CNS-2224687, OAC-2126327, CNS-2146496, CNS-2131826, and CNS-2313190 at the University of Chicago, and Intel and NSF Awards CNS-2003257, OAC-2126327, and OAC-2126281 at UCSB.

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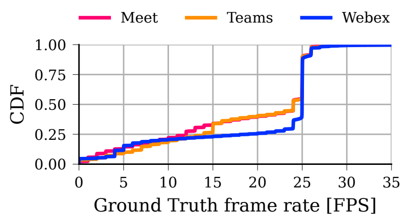
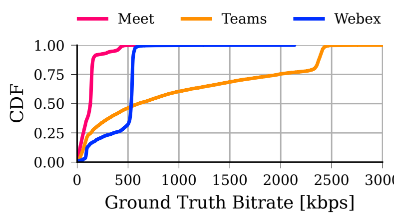
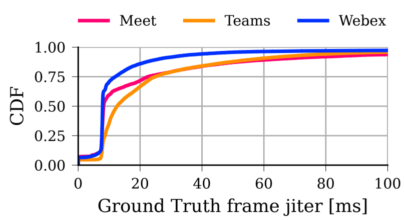


(a) Frames per second

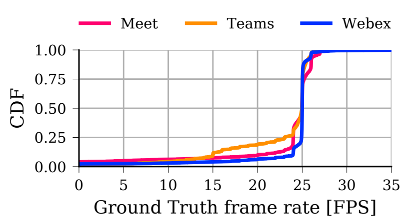


(b) Video bitrate

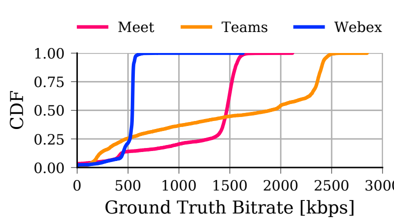


(c) Frame Jitter

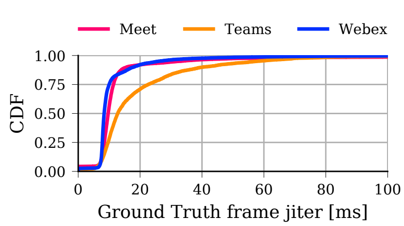
Figure A.1: CDF of ground truth QoE metrics for in-lab data



(a) Frames per second



(b) Video bitrate



(c) Frame Jitter

Figure A.2: CDF of ground truth QoE metrics for real-world data

Actual	**Prediction**		**Total**
	Non-Video	Video	
Non-video	98.2%	1.8%	50,799
Video	0%	100%	946,769

Table A.2: Webex Media classification accuracy for in-lab data

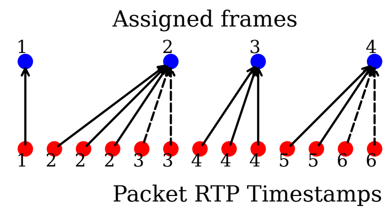


Figure A.3: A plot showing frame assignments by the IP/UDP Heuristic approach over a 1-second window for Meet. The solid arrows represent correct frame assignments while the dotted arrows represent incorrect ones.

Actual	**Prediction**		**Total**
	Non-Video	Video	
Non-video	98.5%	1.5%	378,249
Video	0%	100%	1,818,689

Table A.1: Teams Media classification accuracy for in-lab data

A STATEMENT OF ETHICS

The real-world network traces used in this paper are collected after obtaining approvals from our Institutional Review Board (IRB). We prioritize the protection of user privacy and take extensive measures to ensure it. Our deployment setup solely permits the collection of active measurement data from participants' homes; we can not monitor any user network traffic. More specifically, the Raspberry Pi (RPi) devices used for this study are connected to the home router using a wired connection like any other device. We do not sit in the middle of the user device and the home router. Additionally, we remove any personally identifiable information, such as physical address and demographics, before analyzing the collected data.

The network trace data that we make public corresponds to the VCA calls between the Raspberry Pi and the cloud endpoint. As an additional privacy measure, the IP addresses of both these endpoints have been hashed in the network traces as well as the JSON files obtained via `webrtc-internals`. The remaining datasets used in this paper are collected within controlled lab setting and do not pose any privacy-related issues.

Actual	Predicted			Total
	Low	Medium	High	
Low	90.23%	5.58%	4.19%	573
Medium	14.32%	30.87%	54.81%	447
High	0.89%	3.34%	95.77%	2576

Table A.3: The normalized confusion matrix for resolution predictions by IP/UDP ML model for Teams on real-world data. The percentages indicate the accuracy of our predictions for each frame height.

Method	VCA		
	Meet	Teams	Webex
IP/UDP ML	889.93	114.06	29.53
RTP ML	793.86	167.18	29.22

Table A.4: Bitrate MAE results after using lab-trained models to predict real-world MAE

Method	VCA		
	Meet	Teams	Webex
IP/UDP ML	89.74	64.36	29.78
RTP ML	30.31	19.87	95.43

Table A.5: Frame Jitter MAE results after using lab-trained models to predict real-world MAE

B METHODOLOGY

Algorithm 1 An algorithm for VCA frame boundary estimation using IP/UDP headers only

Input: $packets$, Δ_{size}^{max}, N^{max}
Output: $frames$
  $f \leftarrow 0$
  $frames \leftarrow \{\}$
  for p in $packets$ **do**
    $assigned \leftarrow False$
    for p' in previously seen N^{max} $packets$ **do**
      if $|p'.size - p.size| \leq \Delta_{size}^{max}$ **then**
        $frames\,[p] \leftarrow frames\,[p']$
        $assigned \leftarrow True$
        break
      end if
      if $assigned = True$ **then**
        $f \leftarrow f + 1$
        $frames\,[p] \leftarrow f$
      end if
    end for
  end for

C DATASETS

C.1 Data Description

Figure A.1 and Figure A.2 show the CDF of ground truth QoE metrics for in-lab and real-world datasets respectively.

D EVALUATION

D.1 In-lab Data

D.1.1 Media classification accuracy. Table A.1 and A.2 show the media classification accuracy of Teams and Webex, respectively, using only IP/UDP headers.

D.1.2 Frame rate. Figure A.3 illustrates a case of frame coalescing from one of the Teams sessions. The red dots represent sequence of packets over time with their respective RTP timestamp, while the blue dots show the frame assignment by the IP/UDP Heuristic. Packets with RTP timestamp 2 and 3 have a size of 1022 bytes and 1020 bytes, respectively, leading to these packets grouped into a single frame. Similar is the case for packets with RTP timestamp 5 and 6.

Feature Importance. Figure A.4 and A.5 show the feature importance plots for IP/UDP ML and RTP ML methods, respectively.

D.1.3 Video bitrate. **Feature Importance**. Figure A.6 and A.7 show the feature importance plots for IP/UDP ML and RTP ML methods, respectively.

D.1.4 Frame Resolution. **Feature Importance**. Figure A.8 and A.9 show the feature importance plots for IP/UDP ML and RTP ML methods, respectively.

D.2 Real-world Data

D.2.1 Resolution. Table A.3 shows the IP/UDP ML confusion matrix for resolution prediction for Teams on real-world data.

D.3 Model Transferability

Table A.4 and A.5 show the MAE of models trained using in-lab data and tested on real-world data for video bitrate and frame jitter, respectively.

D.4 Effect of Network Conditions

Table A.6 summarizes the synthetic network conditions emulated to study the effect of network conditions on the accuracy of ML models.

D.5 Effect of IP/UDP Heuristic packet lookback

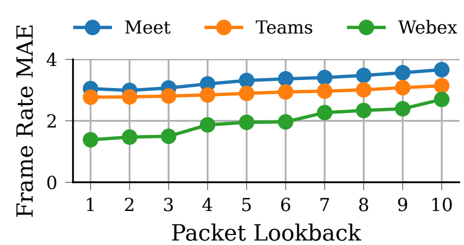
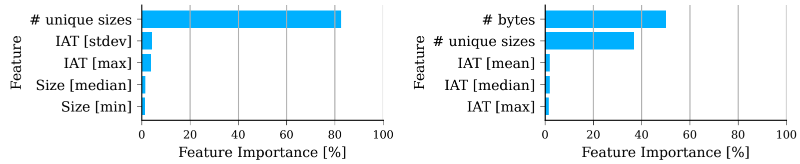


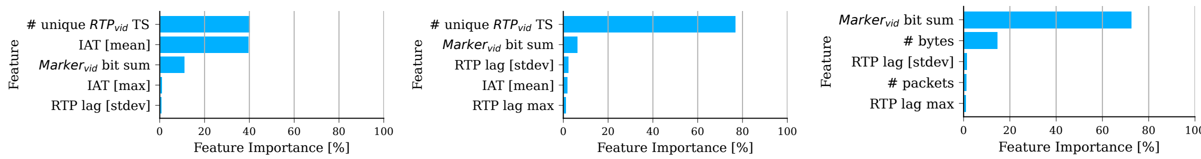
Figure A.10: Variation of frame rate MAE with IP/UDP Heuristic packet lookback parameter

The IP/UDP Heuristic packet lookback parameter was tuned on a sample of 50 in-lab traces each for Meet, Teams and Webex. Figure A.10 shows the variation of frame rate MAE with the number of packets we look back to match a packet with already assembled



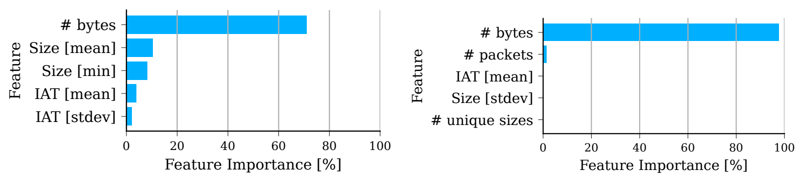
(a) Meet **(b) Webex**

Figure A.4: Top-5 features along with importance scores for frame rate estimation across the three VCAs for the IP/UDP ML method



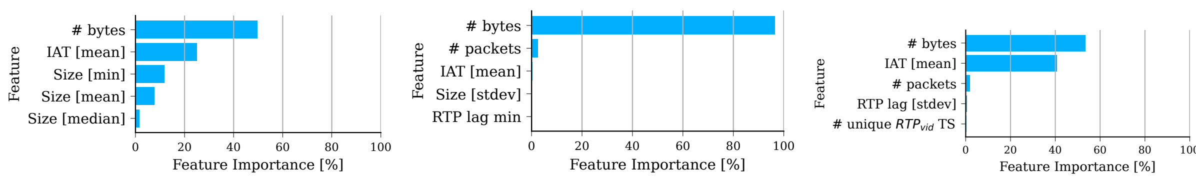
(a) Meet **(b) Teams** **(c) Webex**

Figure A.5: Top-5 features along with importance scores for frame rate estimation across the three VCAs for the RTP ML method



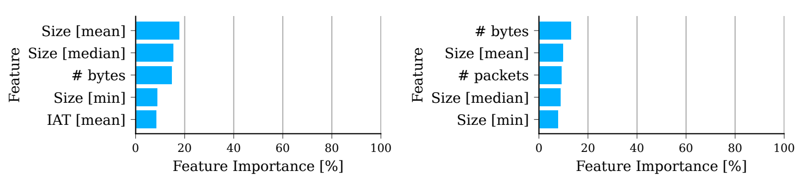
(a) Meet **(b) Teams**

Figure A.6: Top-5 features along with feature importance scores for bitrate estimation using the IP/UDP ML method.



(a) Meet **(b) Teams** **(c) Webex**

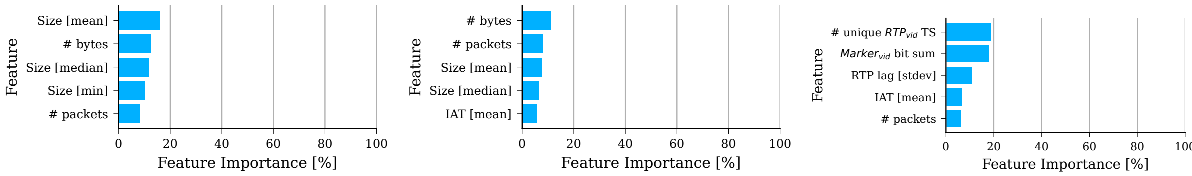
Figure A.7: Top-5 features along with feature importance scores for bitrate estimation using the RTP ML method.



(a) Meet **(b) Teams**

Figure A.8: Top-5 features along with feature importance scores for resolution estimation using the IP/UDP ML method.

frames. For Webex we see a clear increasing trend, while for Meet and Teams we observe minima at lookbacks of 3 and 2 respectively. Webex has an optimal lookback of 1 because 99.70% frames have a maximum intra-frame size difference of 2 bytes, and 99.38% of the



(a) Meet **(b) Teams** **(c) Webex**

Figure A.9: Top-5 features along with feature importance scores for resolution estimation using the RTP ML method.

Impairment	Throughput [kbps]	Delay [ms]	Packet Loss
Mean Throughput	μ : [100, 200, 500,1000, 2000, 4000], σ: 0	μ: 50, σ: 0	0%
Throughput stdev.	μ: 1500, σ: [0, 100, 200, 500, 1000, 1500]	μ: 50, σ: 0	0%
Mean Latency	μ: 1500, σ: 0	μ: [50, 100, 200, 300, 400, 500], σ: 0	0%
Latency stdev.	μ: 1500, σ: 0	μ: 50, σ: [10, 20, 30, 40, 50, 60, 70, 80, 90, 100]	0%
Packet Loss %	μ: 1500, σ: 0	μ: 50, σ: 0	[1, 2, 5, 10, 15, 20]%

Table A.6: Different impairment profiles used for network sensitivity tests. Square brackets indicate a variation across different calls. μ and σ denote mean and standard deviation respectively.

frames are of size less than or equal to 3 packets. Our algorithm is thus able to merge similarly sized frames together by not looking too far back. For Teams, even though 98.56% of the frames have an intra-frame size difference of 2 bytes, only 43.82% have a size less than or equal to 3 packets. Thus, a greater lookback is required to merge similarly sized packets together. For Meet, these percentages are slightly lower than Webex (95.73% and 95.18%), thus the optimal lookback is 2 packets.