

A Predictive DASH QoE Approach Based on Machine Learning at Multi-access Edge Computing

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Abstract—Network operators expected to run on with fast-growing multimedia video streaming (Dynamic Adaptive Streaming over HTTP, aka MPEG-DASH, such as YouTube and Netflix) traffic demand while providing a high Quality of Experience (QoE) to the end-users. The cost, complexity, and scalability of existing QoE estimation solutions have significant limitations to infer QoE from network traffic. However, this work provides an end-user QoE estimation method based on a predictive passive QoE probe mechanism of DASH video using a Machine Learning (ML) approach running at network edge nodes. This work describes the design and implementation of probe configuration at the target edge, with traffic flow monitoring to generate network-level Quality of Service (QoS) metrics. Moreover, build a QoS-QoE correlation ML model in a real-time fashion to detect user equipment traffic patterns to predict user QoE more specifically Mean Opinion Score (MOS).

Index Terms—Quality of Experience (QoE), Quality of Service (QoS), DASH, Machine Learning (ML) , MEC

I. INTRODUCTION

Over the past several years, multimedia traffic precisely MPEG-DASH video traffic becomes the most dominant application on the Internet. According to a recent study and forecast, global Internet video traffic accounted for 70% of the total internet traffic in 2017 [1]. In 2021, it has expected to reach 82% of the entire Internet traffic with immense video traffic growth rates. Hence, it has become a critical issue for video content providers and network operators to manage such amount of video traffic demand and ensure that end-user perceived the best quality. Both content providers and network operators want to provide a great experience to their end-users, known as Quality of Experience (QoE). End-users perceived experience might vary based on various factors, including user context, expectations, and needs. All of the elements have a direct or indirect influence on QoE.

To assess the QoE for any specific multimedia service, active users typically participate in contributing to subjective feedback (Mean Opinion Score) to evaluate the given service [2]. Contrarily, objective methods used to determine objective QoE from a set of metrics to replicate the subjective assessment [3]. Nowadays, the QoE assessment paradigm approaches data-driven analysis [4], where the QoE prediction based on network-level Quality of Service (QoS) metrics through QoS to QoE mapping assessments. Applying the

Machine Learning (ML) method shows the possibility to predict user-level QoE based on the network level QoS even for encrypted traffic [5] [6].

Though content providers have direct access to video quality from the user end, network operators only have access to network traffic for measuring quality. The network traffic mainly collected and analyzed either from the user devices or network elements or both sides to monitor the network quality. The collected data after that used to make QoE estimation/prediction solutions. So-called probes used to capture this data. Probes are monitoring mechanisms that are distributed in various parts of the service delivery chain and gather information about network matrices' performance.

Since network operators have no access to encrypted traffic and assess QoE at the client-side, therefore, present client level QoE monitoring or network level passive monitoring by Deep Packet Inspection (DPI) is not workable for network operators. As an emerging QoE driven architecture, the Multi-access Edge Computing (MEC) [7] leverages the edge computing concept providing low latency and high bandwidth requirements at edge facilities. Beyond the content caching work at edge facilities [8] to optimize the video delivery, no study has conducted yet to estimate/predict QoE by a predictive passive probe running at network edge facilities to meet the immense demand for video traffic.

The aim of this work to proposes a method to predict the QoE, more specifically Mean Opinion Score (MOS) (quantify as 1-bad, 2-poor, 3-average, 4-good, 5-excellent) of target end-users based on passive traffic monitoring at edge facilities near to the target user. We propose to deploy a predictive passive probe mechanism at an edge facility where edge acts as a sink for the corresponding network QoS metrics (e.g., throughput, delay, packets, etc.) of the end-users. After that, a real-time fashion analysis based on the QoS-QoE correlation ML model is used as an predict per video segment QoE (MOS) in contrast to QoS metrics. In the ML part, we evaluate well known supervised algorithms and select the best model. Such QoE prediction helps network operators correlate network traffic with video quality to overcome QoE degradation.

The rest of the paper is structured as follows. In Section II, we present background and motivation. Section III briefly discusses testbed design and implementation, Section IV we

describe data preprocess and analysis, and Section V concludes the paper.

II. BACKGROUND AND MOTIVATION

By providing excellent quality to meet the end user's satisfaction, it is utmost necessary to monitor their satisfaction level from network operators' points. The most common approach to measure user satisfaction relies on QoS metrics collected from the network. QoS defined in terms of some metrics such as bandwidth, delay, packet loss, etc. Therefore, QoS metrics only describe the system's technical performance or service under consideration and leave out user perception and judgment. As a consequence, the concept of QoE developed as a user-centric reflection of QoS. QoE is a user-perceived experience that may differ according to users' expectations and context. The QoE ecosystem influenced by many factors that directly or indirectly affect the user reaction/perception for any service. These influence factors are co-related to each other. In most cases, application-level or objective QoE metrics such as video resolution, bit-rate, and buffering/stall ratio have a strong and positive influence on user QoE. QoS metrics directly affect application-level or objective QoE metrics, which later work as the most influential factor for changing user satisfaction or experience—the relation between network layer QoS and application layer or objective QoE shown in Figure 1. From the network operators' level, most of the influence factors are hardly measurable to predict user QoE, but monitoring network-level QoS metrics are viable.

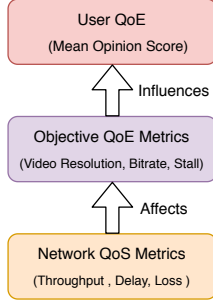


Fig. 1. Relation Between QoS and QoE

Since recent QoE predictions have shifted to a data-driven approach, they rely on statistical/probabilistic and machine learning models; thus, this approach provides objective assessment techniques more ability to give accurate approximation or answer. Machine learning techniques focus on building supervised learning models (1st phase) and making a prediction based on input (2nd phase). At the 1st phase, model trains with QoS metrics and user feedback collecting by a passive monitoring agent named as a probe from the user and network side. In the 2nd phase, predict user experience based on real-time QoS data collecting by a probe without altering the original network traffic based on the previously trained model.

As stated, Dynamic Adaptive Streaming over HTTP (DASH) paradigm has been dominating internet traffic in recent years. DASH provides formats to enable the efficient

and highest quality of streaming service over the Internet. DASH follows adaptive bitrate HTTP streaming standard [9]. Adaptive bitrate streaming is a combination of server and client software that detects a client's bandwidth capacity and adjusts the video stream's quality between multiple bitrates and resolutions. Figure 2, represents the scenario of adaptive streaming. It works by breaking the video media file into a sequence of small HTTP-based file segments. Each segment contains a short interval of playback time of a video with different encoding bitrates, video frame rates, video resolutions, etc. The structure of each video media file has described in a Media Presentation Description (MPD) file, an XML-compatible document. The client automatically decides which of the media segments should be downloaded and playback based on current network conditions as the video playback by a DASH client. The client selects the segment with the highest bit rate possible that can be downloaded in time for playback without causing stalls or re-buffering events in the playback.

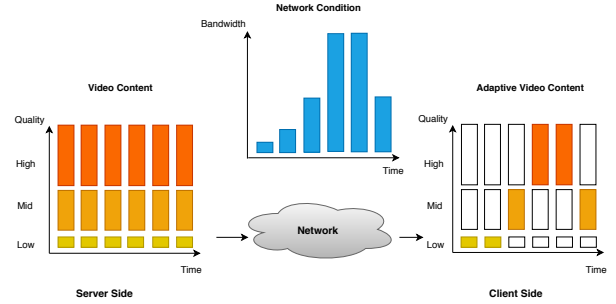


Fig. 2. Dynamic Adaptive Streaming over HTTP

DASH clients are allowed to switch between different video qualities to improve the viewing experience, matching based on current network conditions. Thus, there is a need to be aware of network conditions to optimize video delivery. To optimize the video delivery and meet the user demand, a new technological standard edge computing arises. It allows pushing applications, data, and computing power to the edge of the network. The ETSI promotes a Multi-access Edge Computing (MEC) [7] paradigm to implement the edge computing concept. Our work will focus on network performance and QoE improvements MEC use cases where an analytic MEC function will monitor the traffic information and provide real-time information on traffic requirements of the front/backhaul network. Later, this information passes to the cloud (e.g., cloud edge controller) for reshaping the traffic per application or re-routing traffic as required to improve the QoE. For this purpose, we will propose to deploy a passive probe mechanism at the edge point to monitor the network traffic for inferring the user QoE. This works only to take into account how to predict QoE at the edge node, not about how the network takes adequate action to overcome the QoE degradation..

III. TESTBED DESIGN AND IMPLEMENTATION

This work aims to propose a method based on the deployment of a predictive QoE probe mechanism to allow network

operators to estimate users' QoE at edge facilities without user cooperation and on path middle-box processing. The edge probe periodically collects the bi-direction network traffic (QoS) and predicts users QoE. Figure 3 illustrates the overall network scenario for the QoE estimator probe compound with end-user, access network, core network, internet, and video server. Besides, the access point will serve as the edge computing node use to run a network monitoring probe. Our testbed framework based on four components: (i) emulated network infrastructure with Mininet-WiF [10] (ii) tcpdump packet sniffer agent for passive QoS metrics monitoring at the access point (iii) goDASH [11] player to play DASHb video and generate QoE metrics log file as ground truth (iv) supervised ML model to predict QoE based on QoS features.

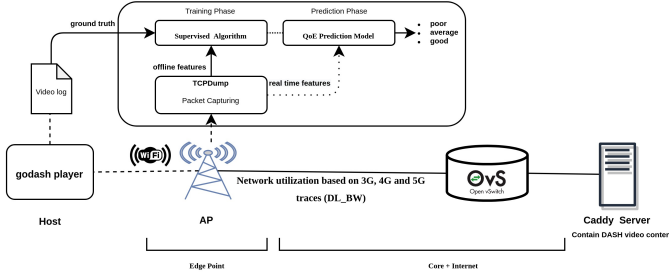


Fig. 3. Network Emulation Architecture

We used the network topology depicted in Figure 3 using Mininet-WiFi along with dynamic network conditions for the entire video session. The testbed consists of one client, a wireless access point (AP), an openvswitch (OVS), and a server. The client linked to access point by wireless and use goDASH player to stream DASH video content. On the other side, a Caddy web server host the animation video Big Buck Bunny (BBB) split into small segments (10-second duration) with different bitrates and resolutions linked with the OVS. The connection between the access point and OVS acts as a bottleneck. Different network conditions are emulated between AP and OVS link by Linux traffic control (TC) tools using downlink throughput parameter from collected 3G [12], 4G [13], and 5G [14] network traces in per the second interval. For each different network traces the client use a goDASH player to stream the same video (10 minutes duration) from the server by throughput based conventional adaptation algorithm. All possible network utilization information during the all streaming experiment are given in Table I.

While streaming video content testbed store the log file generated by goDASH player with adequate per segment QoE metrics (including stall, resolution, and ITU-T P.1203 MOS [15]). Per segment MOS calculated by ITU-T P.1203 [15] approach based on corresponding per segment bitrate, codec, duration, frame rate, and resolution. Simultaneously, testbed captured and stored the network traffic at an access point interface with tcpdump to extract network-level QoS metrics. Figure 4 illustrates the workflow of the entire work, along with pre-processing and analysis steps on generated data.

TABLE I
NETWORK UTILIZATION DURING DATA GENERATION

Technology	Total Traces	Mode	Client	Adaptive Algorithm
3G	15	bus, metro, train, ferry, car	1	conventional
4G	30	static, car, bus, train, pedestrian	1	conventional
5G	9	static, driving	1	conventional

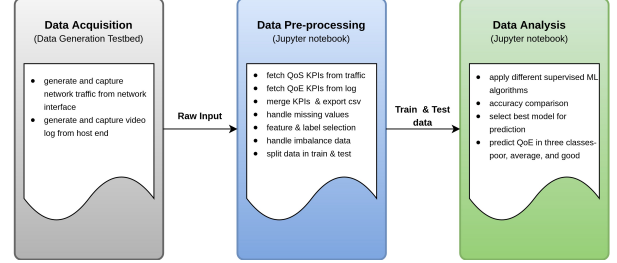


Fig. 4. Workflow

IV. DATA PREPROCESSING AND ANALYSIS

A. Data Preprocessing

To build ML models that predict end-user perceived experience (MOS), more specifically, DASH video performance first, our generated data by testbed requires further processing to be in the form that is acceptable by supervised classification ML algorithms. For this purpose in this section, we present the steps taken to pre-process the captured network traffic and DASH video logged file. The goDASH client used in this work can only provide ground truth (target) of every video segment. Hence, we need to fetch per video segment QoS features from network traffic to build the QoS-QoE correlation model. We observed the pattern of each downloaded segment is persistent in captured network traffic. Each segment request is initiated by HTTP GET request and complete downloading packet of the corresponding request segment from sever until next segments' requests arise. Using this observation, we fetch per segment related QoS metrics (uplink RTT, downlink throughput, and packets), as shown in Figure 5.

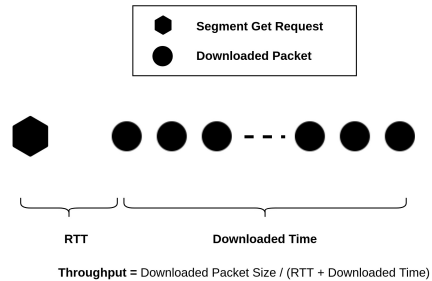


Fig. 5. Segment QoS metrics

The dataset used to make ML model includes both per segments QoS metrics as a feature and QoE metrics from

video log file as ground truth. Video log file provides adequate information of each segment, including bit-rate, stall, resolution, and corresponding segments MOS values. For this work, only MOS values of each segment taken in to account to use a target to build ML models. To ease our classification problem MOS values categorized into three classes as follows:

- Class "Poor" where MOS values between 1 and 2
- Class "Average" where MOS values between 2 and 3
- Class "Good" where MOS values between 3 and 5

The data set contains a total of 3591 instances for each sample per segment video. Figure 6 shows the distribution of instances across classes.

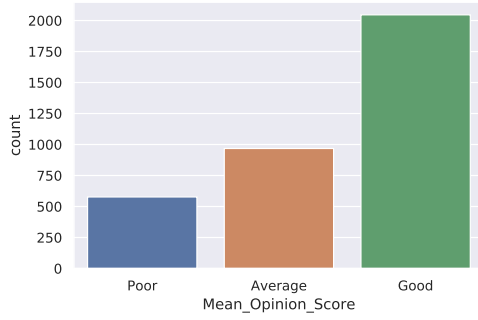


Fig. 6. MOS distribution while imbalance

To build the ML models, we have taken the following steps: (1) Handle missing values by dropping the entire row (2) Balance the number of samples per class by upsampling minority classes using SMOTE (Synthetic Minority Over-sampling Technique) to avoid bias models. The distribution of instances across classes after balance classes are given in Figure 7.

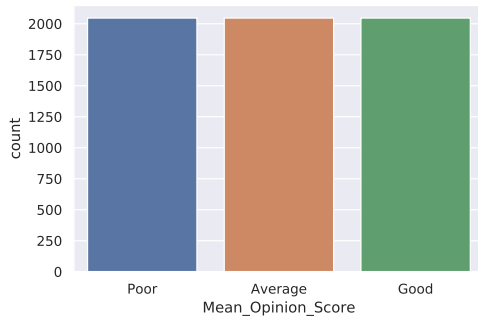


Fig. 7. MOS distribution after balance

(3) After balancing the classes, the dataset split into training and testing in the ratio of 90% and 10%.

B. Model Training and Result Analysis

We evaluated seven well known, supervised ML algorithms models, and select the best model with maximum cross-validation accuracy. To choose the best model, we split our

TABLE II
ML MODELS WITH THEIR CORRESPONDING PARAMETERS

ML Model	Tuned Parameters
Logistic Regression (LR)	penalty='l2', solver='lbfgs'
K-Nearest Neighbors (KNN)	n_neighbors=3
Decision Tree Classifier (DTC)	criterion='entropy', max_depth=None, max_features=None, max_leaf_nodes=None, min_samples_leaf=3
GaussianNB (GNB)	priors=None, var_smoothing=1e-09
Support Vector Classifier (SVC)	C=1, break_ties=False, coef0=0.0, degree=3, gamma='scale', kernel='rbf'
Random Forest Classifier (RFC)	criterion='gini', max_depth=50, max_features=3, max_leaf_nodes=None, max_samples=None, min_samples_leaf=3, min_samples_split=8, n_estimators=500
Multi-layer Perceptron (MLP)	activation='relu', alpha=0.05, hidden_layer_sizes=(100,), solver='adam'

dataset into 90% training and 10% testing dataset ratio. To train the model at first, we tune the hyper-parameters of each algorithm by grid search. Table II presents each of the ML algorithms and their corresponding tuned hyper-parameter.

After tuning the hyper-parameters, a 10-fold cross-validation method used to compare the accuracy among different models. During training each model, cross-validation uses on the training portion dataset. In 10-fold cross-validation, the training portion dataset is split into a 10 number of sections/folds where a portion of fold used as a validation set and the remaining part use as the training set. Thus, each of the models calculated accuracy five times and, lastly, computed average accuracy. Figure 8 presents the average cross-validation accuracy of each of the models.

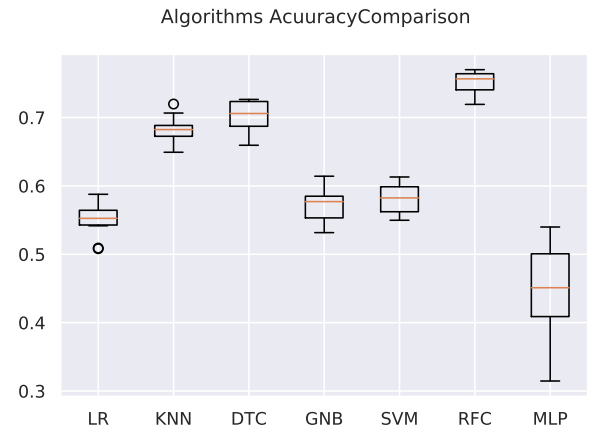


Fig. 8. Result of 5-fold cross-validation

We observed that the model built on DTC and RFC obtained the highest accuracy, respectively 70% and 75%. Hence we opted for the RFC model as the final model. Later, we

TABLE III
MOS CLASSIFICATION REPORT

Class	Precision	Recall	F1-score
Poor	78%	79%	78%
Average	71%	66%	68%
Good	75%	79%	77%

evaluated our train RFC model with the remaining test dataset, and it calculated test accuracy 74%, which is very close to cross-validation accuracy. The classification report in the Table III shows that precision, recall, and F1 score for "poor" and "good" class higher than "average" class.

Simultaneously, if we look at the confusion matrix in Figure 9, we observed that misclassified mostly occurs for "average" class.

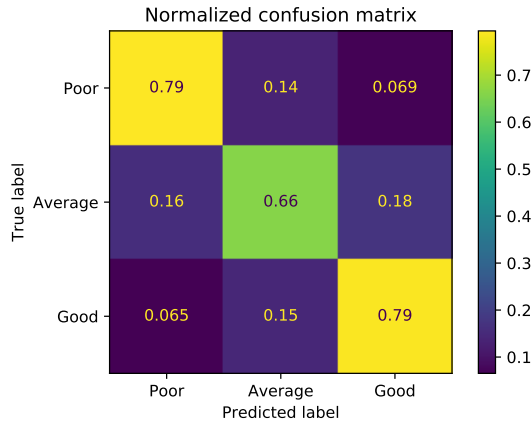


Fig. 9. MOS confusion matrix

Since measured test accuracy is close to cross-validation accuracy, we can conclude our trained model does not suffer from underfitting or overfitting.

V. CONCLUSION

We presented the DASH video QoE prediction approach based on a supervised machine learning algorithm at the edge node in this work. We demonstrated our testbed setup to generate network traffic and capture at the edge interface. Random Forrest supervised model picked as the best model to predict per segment video QoE (MOS according to ITU-T P.1203) based on per segment network RTT, throughput, and packet feature. In the real world, network operators can deploy such trained models to predict real-time QoE and take adequate action to optimize their services. Since network conditions and video quality adaptation logic changes over the time, network operator requires to collect new ground truth continuously, to evaluate the effectiveness of the existing model and retrain with new ground truth data if they are inaccurate. Our overall experimentation approach is reproducible to generate a new dataset or

use the current dataset—the complete experimental information, including data and code available on Github repository (<https://github.com/sajibtariq/reproducible-research-IA369Z>). As future work, it would be interesting to make a more robust anomaly detection and troubleshooting machine learning approach by constructing datasets based on per time slot ground truth and temporal network layer features.

REFERENCES

- [1] V. Cisco, "Cisco visual networking index: Forecast and trends, 2017–2022," White Paper, 2018.
- [2] L. Skorin-Kapov, M. Varela, T. Hossfeld, and K.-T. Chen, "A survey of emerging concepts and challenges for qoe management of multimedia services," *ACM Transactions on Multimedia Computing, Communications, and Applications*, vol. 14, pp. 1–29, 05 2018.
- [3] Y. Chen, K. Wu, and Q. Zhang, "From qos to qoe: A tutorial on video quality assessment," *IEEE Communications Surveys Tutorials*, vol. 17, pp. 1126–1165, Secondquarter 2015.
- [4] R. Huang, X. Wei, L. Zhou, C. Lv, H. Meng, and J. Jin, "A survey of data-driven approach on multimedia qoe evaluation," *Frontiers of Computer Science*, vol. 12, 08 2018.
- [5] I. Orsolich, D. Pevec, M. Suznjec, and L. Skorin-Kapov, "Youtube qoe estimation based on the analysis of encrypted network traffic using machine learning," *2016 IEEE Globecom Workshops (GC Wkshps)*, pp. 1–6, 2016.
- [6] F. Bronzino, P. Schmitt, S. Ayoubi, N. Feamster, R. Teixeira, S. Wasserman, and S. Sundaresan, "Lightweight, general inference of streaming video quality from encrypted traffic," *arXiv preprint arXiv:1901.05800*, 2019.
- [7] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—key technology towards 5g," *ETSI white paper*, vol. 11, no. 11, pp. 1–16, 2015.
- [8] X. Xu, J. Liu, and X. Tao, "Mobile edge computing enhanced adaptive bitrate videodelivery with joint cache and radio resource allocation," *IEEE Access*, vol. 5, pp. 16406–16415, 2017.
- [9] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hoßfeld, and P. Tran-Gia, "A survey on quality of experience of http adaptive streaming," *IEEE Communications Surveys Tutorials*, vol. 17, no. 1, pp. 469–492, 2014.
- [10] R. R. Fontes, S. Afzal, S. H. Brito, M. A. Santos, and C. E. Rothenberg, "Mininet-wifi: Emulating software-defined wireless networks," in *2015 11th International Conference on Network and Service Management (CNSM)*, pp. 384–389, IEEE, 2015.
- [11] D. Raca, M. Manificier, and J.J. Quinlan, goDASH - GO accelerated HAS framework for rapid prototyping. 12th International Conference on Quality of Multimedia Experience (QoMEX), Athlone, Ireland. 26th to 28th May, 2020.
- [12] H. Rüser, P. Vigmstad, C. Griwodz, and P. Halvorsen, "Commute Path Bandwidth Traces from 3G Networks: Analysis and Applications," in *Proceedings of the 4th ACM Multimedia Systems Conference*.
- [13] D. Raca, J. J. Quinlan, A. H. Zahran, and C. J. Sreenan, "Beyond Throughput: A 4G LTE Dataset with Channel and Context Metrics," in *Proceedings of the 9th ACM Multimedia Systems Conference*.
- [14] D. Raca, D. Leahy, C.J. Sreenan and J.J. Quinlan. Beyond Throughput, The Next Generation: A 5G Dataset with Channel and Context Metrics. *ACM Multimedia Systems Conference (MMSys)*, Istanbul, Turkey. June 8–11, 2020.
- [15] Raake, M.-N. Garcia, W. Robitza, P. List, S. Goring, and B. Feiten, "A bitstream-based, scalable video-quality model for http adaptive streaming: Itu-t p. 1203.1," in *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*, pp. 1–6, IEEE, 2017..