# Inclusion of User Behavior and Social Context Information in ML-based QoE Prediction

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Abstract: The widespread use of online video content in every area of the connected world increases the interest in Quality of Experience (QoE). QoE plays a crucial role in the success of video streaming services. However, QoE prediction is challenging as many compelling factors (i.e., human and context factors) impact the QoE and QoE management solution often neglect the impact of social context and user behavior factors on the end-user's QoE. To address these challenges, we have developed a web application to conduct subjective study and collect data from application-layer, user-level, and service-level. The collected data is then used as training set for machine learning models including decision tree, K-nearest neighbor, and support vector machine for the purpose of QoE prediction.

## 1 INTRODUCTION

With the expansion of video streaming services over the internet, mobile video traffic is predicted to reach 79 percent of the overall mobile traffic according to the Cisco Visual Networking Index (VNI) (Ericsson Mobility Report., 2018). This exponential growth is due to the ever-increasing popularity of video streaming services. Content providers such as YouTube, Amazon Prime, and Hulu make decisions on the resource allocation based on both operational costs and user-perceived quality.

Quality of Experience (QoE) is used to enhance the quality of a service based on taking the user's opinion into account and integrating objective Quality of Service (QoS) and subjective influencing factors. A common definition of QoE is cited by the European Network on Quality of Experience as "QoE is the degree of delight or annoyance of the user of an application or a service, it results from the fulfillment of his or her expectations with respect to the utility and/or enjoyment of the application or service in the light of the user's personality and current state." (Le Callet et al., 2012). Based on the above definition, QoE encompasses subjective aspects besides objective parameters. It is a multidisciplinary domain that covers multiple topics such as engineering, social psychology, computer science, etc. Consequently, this variety of research aspects has raised the challenges related to the management of QoE.

As investigating, selecting relevant QoE influencing factors is the first step towards an accurate QoE prediction model (Building function model to map QoE to real number). Through the recent studies, QoE modeling with influence factors including context (physical location) and human factors (user engagement, interests, user profile) in adaptive video streaming services have attracted attention. However, with the ever-growing adoption of adaptive streaming, solutions that rely on in-network measurements to estimate QoE often neglect user behavior and social contextual factors and their impact on the performance estimation as they idealize the user's environment. A lot of research has depicted the influence of application-level Key Performance Indicators (KPIs) on the QoE of videos delivered via the dynamic adaptive streaming over HTTP paradigm. Client-side monitoring can provide the information at the application layer and consequently identifying QoE degradation and according to the analysis conducted with Machine Learning (ML) algorithms (Reiter et al., 2014; Barakovic et al., 2019; Juluri et al., 2015) found that specific application-level KPIs influence the perceived quality: playout resolution, initial delay, average bitrate, and stalling. The underlying

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assumption is that ML-based QoE estimation could be improved with the availability of additional data at application-level information provided by the service provider. We identify three main categories of QoE influence factors that would reflect users' perceived quality:
System-related: information about application-specific parameters such as: buffering, stalling, initial delay, etc.,
User behavior-related: indicates information about user engagement (e.g., time spent watching) and user interaction with the video player (e.g., number and duration of pauses).
Social context-related: information about the popularity (e.g., number of views) of videos and users' preferences (e.g., likes, dislikes).

We put emphasis on to what extent social context and user behavior information could improve QoE estimation and what are the factors that have high influence on the end-QoE this besides specific cause analysis and efficient QoE management.

In this work, we choose YouTube social platform for data gathering to obtain as much information about the user-generated data on YouTube and to show how exploiting social context and user behavior information could improve the performance of QoE estimation models.

To address this issue, we develop a crowdsourcing framework to monitor and collect information on video streaming services. The monitoring probe is a web application that embeds YouTube videos, we study the relation between application-level KPIs, user behavior, and social contextual parameters, conduct features selection, and build a QoE model based on machine learning to estimate QoE Mean Opinion Score (MOS) based on highly correlated features related to objective and subjective aspects.

The remainder of this paper is structured as follows. Section 2 provides an overview of the state of art on monitoring and estimating video QoE. Section 3 promotes our contributions. Section 4 reports on the QoE prediction algorithms and discusses models' performance results. Conclusion and perspectives are discussed in Section 5.

## 2 RELATED WORK

To develop an efficient QoE model it is crucial to identify which factors cause network degradation and influence most perceived QoE. QoS fluctuation can occur in different parts of the video streaming transmission chain. Encryption of video traffic transmitted over the internet is increasing. Thus, the monitoring solutions should be deployed at the client-side instead of different parts on the network (e.g. user equipment, home/access network, core network). To monitor video streaming service on the user-side, (Wamser et al, 2015) developed a passive android application to measure the application level KPIs (i.e., video resolution, buffer, bit rate) of YouTube videos in the user's mobile device, another application for mobile services called YOUQMON (Casas et al., 2013) was proposed to estimate MOS of YouTube videos in 3G networks from passively analyzing the traffic. Stalling events are calculated in real-time using the QoE model and projected to MOS values. In the same vein, (Maggi et al., 2019) proposed a technique to detect stall events and classify them into stalling caused by poor network quality or user-seeking interactions. It is important to identify root cause analysis to take immediate actions such as fair reallocation of resources in case stalling caused by network conditions. Hence, crowdsourcing is considered to enable new functionalities to subjective evaluation, it is more time and cost-effective, flexible and it creates realistic test environment, One initiative in the direction of collecting wide-scale video streaming usage information for popular video streaming services (e.g. YouTube, Amazon Prime Video, Netflix) (Robitza et al., 2020) have developed a web browser extension called YTCrowdMon. In most recent research, the potential of ML techniques has been exploited for KPI and QoE estimation of encrypted traffic from network/application-level metrics. (Dimopoulos et al., 2016) developed an ML-based model to detect QoE degradation from encrypted traffic. They used the Random Forest algorithm to classify video streaming sessions regarding three metrics that influence adaptive video streaming QoE. i.e. stalling, the average video quality, and quality variations. In a more similar approach, in (Orsolic et al., 2017) a system called YouQ is developed to monitor application-level quality features and corresponding traffic traces per video session to classify YouTube videos using various models into three QoE classes ("low, medium, high", and "low, high"). Instead of technical indicators, there is another influence metric that can be deemed worthwhile, indirect metadata of different sources.

Contextual factors can reveal an important amount of information on the quality of the transmission chain and content of interest. Also, User engagement which describes the viewing time of video streaming has been used as a replacement for subjective QoE. (Moldovan and Metzger., 2016) investigated the correlation between QoE and user engagement for on-demand video streaming services, and the results show a strong correlation. A large-scale study was conducted in (Shafiq et al., 2014) to characterize mobile video streaming performance and study how user engagement impacts to network and application Key video performance metrics from the perspective of a network operator. They proposed a model to predict video abandonment based on a strong correlation observed between several network features and abandonment rate. Other metrics that depict social context factors include popularity, the number of like-dislike, and the number of comments. These features are usually applied on a video level and contribute to the quality perceived by users. (Wu et al., 2018) investigated the relationship between the videos with high engagement and view count using large-scale measurements of YouTube metadata videos collected over two months, they found engagement metrics more stable and predictable compared to popularity metrics which are driven by external promotion. In a similar work, (Park et al., 2016) demonstrated a positive correlation between video watching, comment sentiment, and popularity metrics. In a realistic environment, users interact with video players while watching videos, examples of user interactions are pausing, playing, seeking, change display quality. (Seufert et al., 2019) incorporated user interactions when building ML models for QoE analysis of encrypted traffic in real-time. While (Bartolec et al., 2019) have trained ML models on data with and without user playback related interactions to investigate how user interaction could impact QoE/KPI estimation.

# 3 METHODOLOGY

## 3.1 Dataset and Crowdsourced Measurement

The goal is to provide a measurement tool to monitor specific Key Performance Indicators (KPIs) that correlate with the perceived quality during a YouTube session. We build a web QoE monitoring application for YouTube crowdsourced QoE measurements. The tool displays the same functionality as the native YouTube client app. It gathers information from user-level, service-level, and application-level using APIs (e.g., Google, YouTube Data) and built-in functions. Figure 1 shows the testbed used for data collection.
One hundred individuals participated in the experiment. The participants were randomly selected from SUP COM school within a university context. They had invited other people who had prior experience using a web application to conduct the experiments. Written instructions were provided. They are asked to insert their personal information: age, gender, preferences to create a session. Afterward, they watch videos according to their preferences and rate the perceived quality multiple times. Figure 1 illustrates the diagram of the QoE experiment testbed.

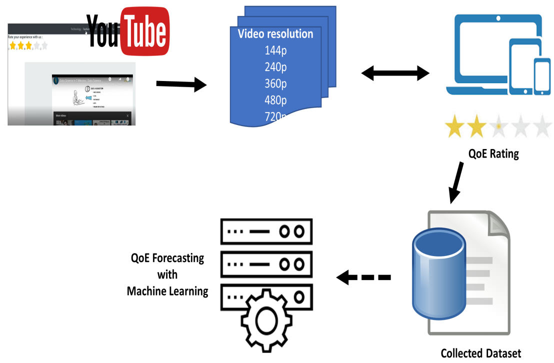



Figure 1: Proposed QoE forcasting methodology.

The dataset we collected consists of application-level features, social context parameters, and user behavior over videos. Table 1 depicts the metrics reported by the monitoring app. The monitored application-level data are the most relevant KPIs for QoE in HTTP adaptive video streaming as initial delay, buffering, stalling, and quality changes (Wamser et a., 2015). We captured data that is related to user behavior. User engagement describes the percentage of the video viewed. We addressed one type of user interaction with the video player which is the user-initiated action to pause the video. Social context factors cover popularity and preferences data extracted from YouTube metadata information (e.g., number of views, like and dislike, etc.). To label the played videos with MOS, the participants were asked to rate the perceived quality.
We collected 1200 data records for four months containing the subjective and objective measures (Table 1). to create a homogeneous dataset from crowdsourcing tests we filtered out the invalid measurements and unreliable instances. After cleaning the data set we obtained 1010 instances each contains 20 features.
With the new dataset, we can figure out what impact QoE and build a model based on ML algorithms that predict accurate MOS values.

## 3.2 Dataset Characteristics

To study the impact of social context indicators and user interactions on the end-users QoE we analyzed the collected data. Figure 2 describes the distribution of the relevant features for the quality assessment. It

Table 1: Main features of the dataset.

| Category | Features |
|---|---|
| **Application-level information** | Initial delay, etc. |
| | Buffer level, avg buffer level, etc. |
| | Stalling, total stalling length etc. |
| | Quality switches, Avg bitrate etc. |
| **QoE rating** | MOS value, content rating |
| **User behavior** | Watch time ratio. |
| | Pause events |
| **Social context** | View count, Like/dislike count, Category title |

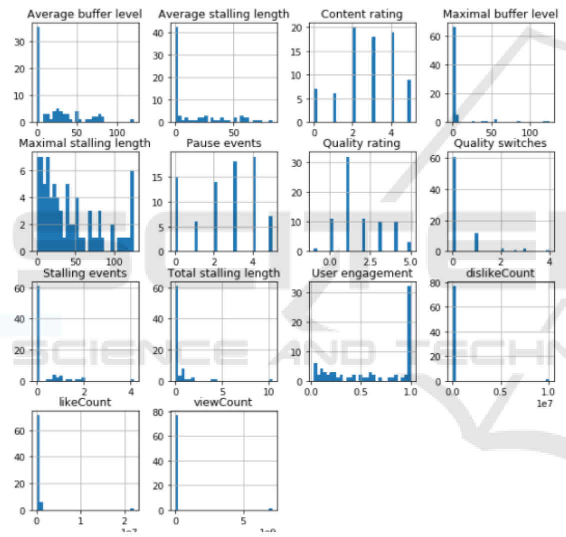



Figure 2: Relevant features.

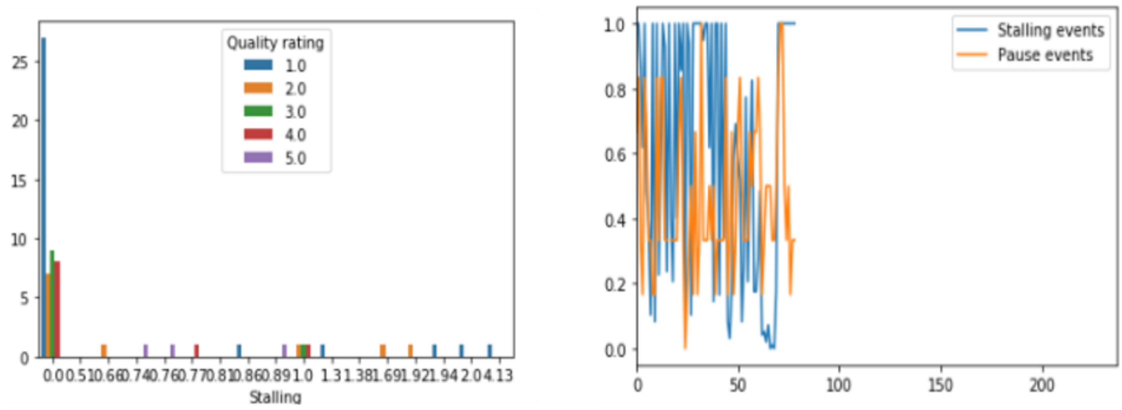
shows that the users prefer to watch highly viewed videos which led to higher content ratings and better-quality ratings, they tend to give high rates to videos with a large view count and that confirms the positive correlation between content popularity and MOS considering network transmission. Also, a negative relationship exists between pause events and MOS (Quality rating). In most of the videos viewed, we reported the occurrence of stalling events because of drastic bandwidth changes. We identified a correlation between user engagement and quality rating given the fact that a previous study (Park et al., 2016) has identified this relation. Thus, we observed that the more the user spent time watching more the MOS rating is high. To understand the relationship between multiple features, Figure 3 shows the distribution of the overall stalling and pause events, it can be noted that in most videos when stalling happens, users tend to pause the video for buffering to improve the streaming quality. Figure 3 confirms that stalling impacts perceived quality as the users give a low rating when stalling occurs. In the end, we can assume that user behavior, user interaction, and content-related information influence the perceived quality as much as the stalling.

## 3.3 Data Preprocessing

In this section, we conduct feature selection and feature importance to help build an efficient ML model. The model training component takes relevant application-level, service-level, and user-level data as input data. First, the former data is extracted using APIs and fed to the feature selection algorithm to select the exact features and labels to be used for the training of ML models. The collected data is used as input to the feature selection algorithm to reduce complexity and improve the performance of the predictive models by eliminating irrelevant features from the dataset.

The pertinent features to be utilized are specified by the feature selection algorithm. In our work, we relied on the univariate selection method SelectKBest provided by scikit-learn library. This method enables the selection of k highest scoring features that have the strongest relationship with the output feature based on univariate statistical tests. The algorithm reduced the number of features to 14, they are listed in Figure 4. The most commonly selected variables are related to features from different levels. The selected features from the application level are mostly the features that were selected in other work (Abar et al., 2017; Casas et al., 2013; Ben Letaifa., 2018; Ben Letaifa., 2019) and influence on the end QoE. Our findings show similar results presented in the research area. In the case of popularity metrics and user behavior and regardless of feature selection algorithm popularity metrics have been proved to be highly related and influence the perceptual quality. Specific user behavioral and engagement metrics were also selected by the selection algorithm as they have a relationship with the perceived quality.

To highlight which features may be most relevant to the output MOS, we used two commons classifiers Random Forest (RF) and XGB Classifier to provide an estimation of feature importance for a predictive modeling problem. XGB algorithm decides on features' importance based on how many times that feature is used to make key decisions across all the trees. RF as opposed to XGB method evaluate relative im-




(a) stalling/MOS.

(b) Pause events/Stalling events.

Figure 3: Data Visualization.

portance scores for each feature separately. Figure 4 shows results in terms of feature importance with the two used algorithms. In subfigures, 4a and 4b the importance of features in the feature list differs. It can be observed that features with less important scores are different but still relevant such as popularity indicators. Although, important features are almost the same depending on whether RF or XGB was utilized. The user behavior (pause events) and popularity indicators contribute equally to the model performance.
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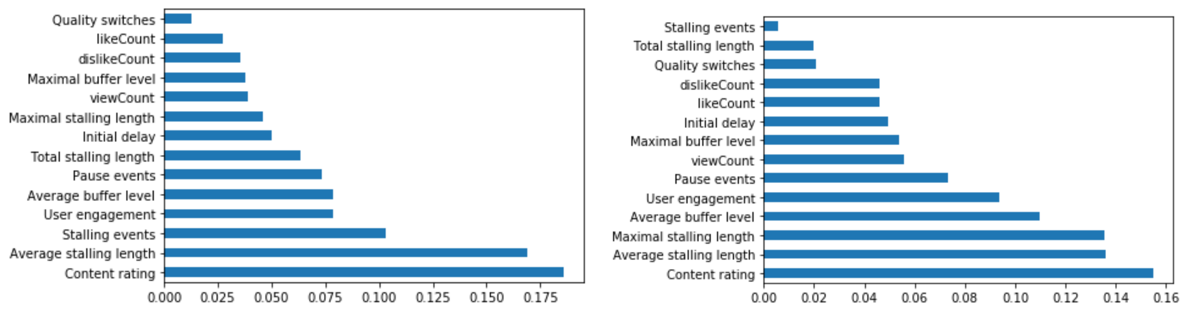
### 3.4 Model Training

In this section, we conduct a feature selection study to select pertinent features and we build a machine learning model that predicts accurately QoE. to define our model, we go with step 1: we use cross-validation method to split the dataset into three subsets: training, validation, and testing. This method is more effective than splitting the dataset in training and test data because it prevents problems like overfitting. In step 2: to predict MOS using the most used prediction models in literature: K Nearest Neighbor, decision tree, and random forest. we applied a set of hyperparameters aiming to find the right combination of values that can help maximize the accuracy. In step 3, we evaluate the performance of our models by measuring accuracy, Pearson correlation, and F1- score. We end up by selecting the algorithm that gives us the best prediction of MOS. We build two ML-based models to show how social contextual info and user interactions enhance the performance of QoE estimation. The models are trained on: Model1: Application-level data, user engagement indicator Model2: Application-level data, user behavior info, and social contextual factors. Training ML models using dataset plays a crucial role to understand the mathematical endeavor and create the right output. In this work, we use algorithms: Random Forest, K-Nearest Neighbor (KNN), and Decision Tree (DT), description of the former ML algorithms and training phase will be discussed in the following. KNN solves regression and classification problems by classifying data points based on similarity measures, it categorizes data regarding the classes of their closest neighbors. to train KNN model, Euclidean metric with equal distance weights has been selected as the distance metric, and to avoid overfitting, a cross-validation technique has been used when using different values of K. the performance of KNN has been presented in Table 2. Random forest inspired by the DT algorithm; it is a special case of bootstrap bagging applied to the decision tree. For model training and from the literature we found the family of tree-based algorithms perform best (Bartolec et al., 2019; Orsolic et al., 2017; Wamser et al., 2015). For the case of in-network applications, we argue to use decision tree and random forest as it requires fewer resources and




(a) Features selected, XGB model.

(b) Features selected, RF model.

Figure 4: Features importance using classification models.

exhibits good performance.

# 4 EXPERIMENTAL RESULTS

## 4.1 Performance Evaluation Metric

In this section, we provide a description of performance evaluation metrics. For objective quality assessment, we use statistical metrics that cover aspects: linearity, accuracy, and consistency against subjective data. The statistical evaluation metrics we used are summarized as follows:
**Accuracy** The accuracy is the fraction of the number of correct predictions and it is defined as (Eq.1): where $x_i$ is the ground truth, and $y_i$ is the predicted value, n denotes the number of samples.

$$A = \frac{1}{n}\sum_{i=1}^{n} f(x_i, y_i) \quad (1)$$

**F1 score** measures the test accuracy it can be interpreted as the weighted mean of precision and recall, it provides a standard scale of [0, 1] and F1 score (Eq.2) reflects the robustness of the classifier.

$$F1 = \frac{TruePositives}{TruePositives + \frac{1}{2}(FalsePositives + FalseNegatives)} \quad (2)$$

**Pearson Linear Correlation Coefficient (PCC).** PCC measures the linear correlation between model's output and the subjective QoE. The range of PCC(Eq. 3) is [-1, 1] where 1 indicates positive correlation and -1 negative correlation.

$$PCC = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (3)$$

Yi denotes predicted MOS and xi the subjective one. N indicates the total number of samples.

Table 2: Experiment results of Model2.

| **Classifier** | **Accuracy** | **F1 Score (*macro-avg*)** | **PCC** |
|---|---|---|---|
| *RF* | 0.875 | 0.54 | 072 |
| *KNN (neighbor = 5)* | 0.77 | 0.27 | 0.56 |
| *KNN (neighbor = 10)* | 0.812 | 0.30 | 0.62 |
| *KNN (neighbor = 15)* | 0.812 | 0.30 | 0.62 |
| *DT* | 0.979 | 0.76 | 0.883 |

## 4.2 Evaluation

We evaluate the performance of QoE models. Table 2 and Table 3 show the performance of classification models. In the case of model1, our results show that Decision tree gives the best results which makes it a perfect candidate for QoE prediction system implementation. RF learning algorithm shows results better than KNN although trying different values of neighbors more than 10 didn't enhanced the performance of the algorithm. On the contrary, the model which learns features from contextual, user behavior data besides application KPIs performed better than model trained only with application-level parameters. For model2 DT algorithm shows the best results.

# 5 CONCLUSION

In this work, we presented a WebQoE monitoring approach and an applied test methodology based on real time QoE estimation depicted by end users. based on large dataset collected using WebQoE application a solution has been proposed using decision tree clas-

Table 3: Experiment results of Model1.

| Classifier | Accuracy | F1 Score (*macro-avg*) | PCC |
|---|---|---|---|
| *RF* | 0.790 | 0.47 | 061 |
| *KNN (neighbor = 5)* | 0.50 | 0.15 | 0.35 |
| *KNN (neighbor = 10)* | 0.612 | 0.20 | 0.35 |
| *KNN (neighbor = 15)* | 0.612 | 0.23 | 0.35 |
| *DT* | 0.779 | 0.56 | 0.653 |

sifier to predict QoE in the context of adaptive video streaming services. For future work we aim to develop QoE management approach of video services in SDN/MEC environment where we can implement our QoE prediction model as in-network solution. our ongoing work will focus on QoE management and control approach for video streaming services delivered over the emergent network technologies.

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