

On user-centric QoE prediction for VoIP and video based on machine-learning

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Abstract: Assessing the impact of different network conditions on user experience is important for improving the telecommunication services. We have developed the MLQoE, a modular algorithm for user-centric QoE prediction. The MLQoE employs several machine learning (ML) algorithms and tunes their hyper-parameters. It selects the ML algorithm that exhibits the best performance and its parameters *automatically* given the input. The input consists of metrics based on empirical measurements. The MLQoE has been extensively evaluated in the context of VoIP. To assess the generality of our methodology, we have also evaluated the MLQoE using bidirectional VoIP and video traces. The MLQoE outperforms several state-of-the-art algorithms, resulting in fairly accurate predictions. Currently, we have been applying the MLQoE in the context of a video streaming service in a production environment of a large telecom operator in Greece.

Note: This paper is based on our work entitled “On user-centric modular QoE prediction for VoIP over wireless networks based on machine-learning algorithms”, by Paulos Charonyktakis, Maria Plakia, Ioannis Tsamardinos, and Maria Papadopouli, that will appear in the IEEE Transactions on Mobile Computing.

1 INTRODUCTION

The impact of the network performance on the quality of experience (QoE) for various services is not well-understood. The QoE can be defined as “the degree of delight or annoyance of a person whose experiencing involves an application, service, or system. It results from the person’s evaluation of the fulfillment of his or her expectations and needs with respect to the utility and/or enjoyment in the light of the person’s context, personality and current state” [5]. This definition reflects some of the user-centric and contextual aspects of QoE. In general, depending on the type of service and the context, the QoE can be affected by various techno-socio-economic-cultural-psychological parameters, e.g., by the user preferences with respect to QoE and price, willingness-to-pay, and intrinsic indicators towards a service provider (e.g., brand name, perceived value, reliability), its content (e.g., richness, diversity, searching mechanisms), and even integration with other popular services (e.g., social networking applications). It may be difficult to dynamically capture these aspects and assess to which extent they affect the QoE of a service, especially in a non-intrusive manner. Thus, the design of the appropriate metrics and methodologies to monitor the infrastructure (e.g., network, system, and context), collect the appropriate data, and model the QoE can be challenging.

Our community has been assessing the impact of the network on the user experience, which is critical for improving the telecommunication services. A diagnostic tool that indicates whether users perceive the deterioration of the network performance can be very useful. When users do not perceive performance degradation, an adaptation could be avoided. Moreover for churn prevention, cost reduction, increasing revenue, rolling out new services and differentiating their existing ones, the knowledge about the user engagement and satisfaction is important in order to create competitive advantages within the Internet market.

Characterizing the QoE for VoIP, video streaming, and web browsing, has been at the epicenter of various activities. For example, the prediction of QoE for VoIP can be performed by applying mathematical models based on QoS parameters, signal processing techniques, or data-mining algorithms. The majority of such efforts aim to characterize the user experience, analyzing various types of measurements often in an aggregate manner.

We recently developed the MLQoE, a modular algorithm for user-centric QoE prediction. The MLQoE employs multiple machine learning (ML) algorithms, namely, Artificial Neural Networks, Support Vector Regression machines, Decision Trees, and Gaussian Naive Bayes

classifiers, and tunes their hyper-parameters. It selects the ML algorithm that exhibits the best performance and its parameters *automatically*, given the input. The input involves network and systems metrics based on empirical measurements. The MLQoE has been extensively evaluated in the context of VoIP over wireless networks under various network conditions and feedback from subjects (collected in field studies). It integrates also subjective opinion scores collected from users in the context of field studies or via crowd-sourcing tools. Moreover, we performed a preliminary analysis to assess the generality of our methodology using bidirectional VoIP and video traces. We showed that the MLQoE outperforms several state-of-the-art algorithms, resulting in fairly accurate predictions. Currently, we have been applying the MLQoE in the context of video streaming services in a production environment of Forthnet, a large telecom operator in Greece [62]. Section 2 overviews the related work, while Section 3 presents the MLQoE. In Section 4, we discuss the main results in the context of VoIP, while Section 5 presents a brief discussion on video streaming and suggests research directions.

2 RELATED WORK

There were efforts to distinguish the metrics with dominant impact on the performance of certain applications and the conditions that substantially degrade their performance as perceived by users [3]. For example, our early work [6], [7] statistically analyzed the impact of network conditions (e.g., handover, heavy UDP, and heavy TCP traffic), different codecs (e.g., AMR, G.711) on the estimated quality of user experience of VoIP using ANOVA and Tukey's HSD criterion. The analysis revealed highly statistical significant differences between the estimations of the E-model and PESQ, as reported by the Student's T-test ($p < 0.01$). This motivated the need for a more thorough statistical analysis with larger datasets. In general, the prediction of QoE for VoIP can be performed by applying mathematical models based on QoS parameters (e.g., E-model [8], WFL [9]), signal processing techniques (e.g., PESQ [10]), or data-mining algorithms (e.g., non-linear regression models [11], [12]). The E-model is based on packet loss and end-to-end delays considering also other factors, such as voice loudness, background noise, equipment impairment, packetization distortion, and codec robustness. It produces a rating, the R-factor, that estimates the voice quality. The Weber Fechner Law (WFL) [9] indicates the relation of QoE and QoS ($QoE = \log(aQoS + b)$). Reichl et al. [14] applied the WFL to model the QoE as a function of the bitrate (using logarithmic regression) in the case of Speex codec. An "inversion" of the WFL, the IQX hypothesis uses exponential regression. Unlike the above methods that integrate directly QoS metrics, the PESQ estimates the perceptual difference between two audio signals, assuming that the samples are temporarily synchronized and of 6 s to 20 s duration. Classification and regression methods based on ML and statistical analysis have also been employed for the prediction of QoE. These methods assume as "ground truth" the MOS that the E-model or PESQ reports. Thus, their estimations propagate the error of the E-model and PESQ [11], [12], [16], [17], [18], [19]. Typically, studies that perform subjective tests estimate the performance of their models using the simple hold-out estimation [20], [21] or the cross-validation algorithm [22], [23], [24].

The analysis of QoE for video has also received a lot of attention. For example, Krishnan and Sitaraman [27] used statistical tests (e.g., Pearson, Kendall) to evaluate the QoE based on user engagement, abandonment rate, and frequency of visits. Other studies use the PESQ or VQM [28], ML algorithms with hold-out estimation [29], [30] or with cross-validation [31]. Simple regression models have been also used in order to characterize the user satisfaction [32], [33]. The role of the context on QoE for various streaming services has been highlighted in several studies (e.g., [3]). The evaluation of acceptance, satisfaction, entertainment, and information recognition in different contexts (e.g., train station, bus, cafe) using ANOVA, Pearson correlation, Spearman, and Chi-square was the focus of [34]. The context and the repeatability of the experiments was analyzed in [35]. In the context of video streaming and telepresence, Wu et al. [36] characterized the QoS based on interactivity, vividness and

consistency and the QoE using as metrics the concentration, enjoyment, telepresence, perceived usefulness, and perceived easiness of use. It then mapped QoS to QoE by applying Pearson's correlation. Note that all the aforementioned models estimate the QoE for an average user in contrast to MLQoE that can be employed to capture also the individual user preferences. In general, the ground-truth for the QoE has been formed based on either the explicit opinion scores reported by users (e.g., in the context of listening tests/controlled studies or at the end of their service via a GUI, as in the case of skype) or based on measurements collected using physiological metrics [37], [38].

3 MLQoE algorithm

The MLQoE uses supervised regression, in which the predictors are metrics (e.g., based on jitter, packet loss, rebuffering, startup delay, bitrate changes) and the predicted outcome is the QoE score. The predictors are determined depending on the specific service, size of the collected data, characteristics of the testbed and measurement study. The performance metric could be the absolute difference of the predicted QoE score compared to the actual score provided by the user (which can serve as the "ground truth"). The MLQoE consists of several steps, including the normalization, feature selection, training multiple regressors, the selection of the best ML model and the estimation of its performance. It employs a set of ML algorithms, which can be easily extended to incorporate other ML algorithms. The MLQoE has two main phases, namely, the model selection and performance estimation. The model selection takes as input the training set of the performance estimation loop, cross-validates it, and reports the best model. The performance estimation obtains as input the dataset, partitions it into folds, estimates the performance of the best model (that the model selection outputs) in each fold and reports (as output) the mean error for the dataset.

To address the high dimensionality of the data (i.e., reduce the number of network and systems metrics that have to be measured), the MLQoE employs causal-based and Bayesian Network-based feature selection methods to identify the metrics that have a dominant impact on QoE. Unfortunately, estimating the performance of multiple models on the same test set leads to overestimation of the performance of the best performing model. To provide a conservative estimation, while at the same time avoid underfitting, the MLQoE employs the Nested Cross-Validation (nested CV) protocol [26]. Notice that, the data normalization and feature selection is executed inside the nested CV.¹

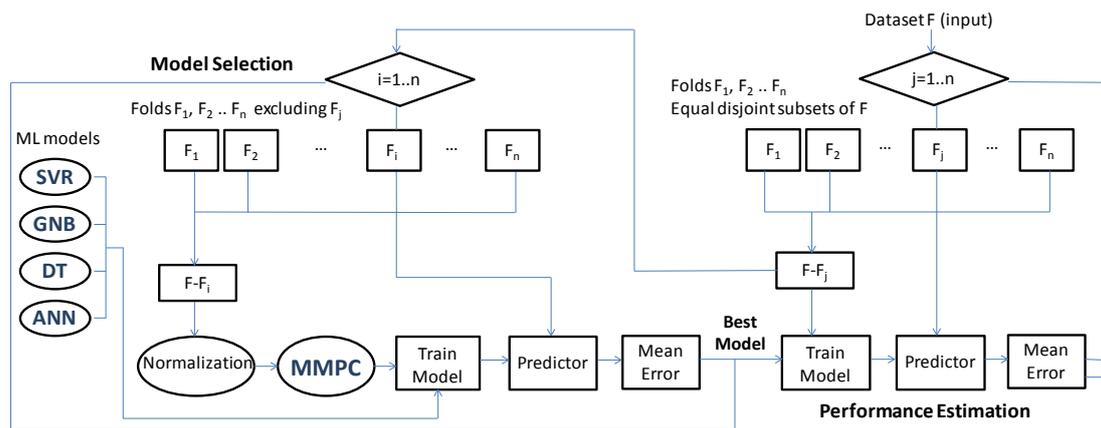


Fig. 1 An overview of the main modules of the MLQoE.

¹ The runtime phase of the MLQoE (and all the ML algorithms) is of negligible computational complexity in practice, specifically SVR $O(m)$, GNB $O(1)$, DT $O(\log(e))$, ANN $O(m)$, E-Model $O(1)$, Normalization $O(m)$ (m is the number of the network metrics and e the number of examples in training phase). In contrast, their training phase is of relatively high computational complexity (especially, in the case of SVR, and ANN) though is performed off-line. The complexity of the E-model is low, while PESQ has a high computational complexity [10].

4 MLQoE EVALUATION

The MLQoE was extensively evaluated in the context of VoIP. The analysis distinguishes the packet loss as the dominant network metric that affects the user satisfaction and demonstrates the benefits of the user-centric modular aspects of the MLQoE. The MLQoE was trained per user and can predict the user opinion score with a fairly accurate manner (e.g., mean absolute error of less than 0.5 and median absolute error less than 0.3 in the MOS scale). Moreover, the MLQoE outperformed the E-model and PESQ, and their differences were statistically significant in most cases. To highlight further the impact of the user-centric approach, we also applied the MLQoE in an aggregate manner. Indeed, the aggregate approach reports a significantly higher mean error. An advantage of the MLQoE over the WFL and IQX is its robustness on the number of dominant factors for the prediction of QoE. The WFL and IQX consider only one factor, while the MLQoE integrates the set of the dominant network metrics, reported from the feature selection algorithm. The analysis also reported the presence of users that were consistently strict or lenient on their evaluations throughout the study.

5 DISCUSSION

We have developed a testbed for monitoring and collection of network and systems measurements as well as feedback from users in the context of the NovaGo video streaming service that Forthnet, a major Greek telecom operator provides [62]. A mobile app, running on the smartphone of the user (client), monitors the network and collects log messages generated by the Nova GO client, when the user performs certain actions. The monitoring is performed in the background. At the end of a session, the user rates its experience via the mobile app by providing an opinion score. The analysis of the collected data determines various events (e.g., bitrate and resolution changes, buffering, user actions with respect to video sessions and service) and forms a rich set of metrics. The MLQoE will be applied on the collected network, systems, and user opinion scores for developing user centric QoE models for this service. The field study is still in progress. The analysis will start later this month. In a separate project, in the context of crowdsourcing QoE-based recommendation systems, the MLQoE has been employed to detect inconsistencies and random values in the opinion scores that user provided and treat them appropriately.

The development of non-intrusive reliable methodologies for assessing the QoE in the context of telecom services is a fascinating area of research. Let us conclude by briefly indicating some challenges and issues that need to be addressed: It first requires a better understanding of the impact of various contextual (e.g., location/premises, time, presence), cultural, social and economical (e.g., cost of service, willingness-to-pay) aspects on the QoE. However the incorporation of such aspects in the QoE prediction/modeling can be challenging. Researchers have been aiming to infer the user experience, engagement, or satisfaction from a rich set of traces (e.g., logs, physiological data), collected from various applications (e.g., social networking) or using hardware (e.g., cameras, microphones) and various modalities. However the collection of data and user feedback, that will serve as the ground truth (e.g., in training the models), in a *non-intrusive* manner involves many open questions. Moreover, the provision of the appropriate incentives (e.g., micropayments, credits, free calls) for strengthening the user participation (e.g., in field studies, crowd-sourcing and participatory systems) needs to be addressed. Furthermore, field studies and data collection processes should adhere standard guidelines. The protection of user privacy in the context of such data collection studies should be ensured. A proper data sanitization (e.g., detection of unreliable, erroneous or censored data, treatment of missing values and anomalies) is also crucial for obtaining meaningful results. Clearly these issues trigger a plethora of open interdisciplinary questions and engineering problems. The proposed solutions and methodologies can potentially serve as a basis not only for other telecom services but also for a broader set of services and applications.

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