Machine learning based Quality of Experience (QoE) Prediction Approach in Enterprise Multimedia Networks

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Abstract: In this paper, we discuss quality of experience in multimedia networks. We present an architecture and a survey of machine learning methods to predict the quality of experience in an enterprise multimedia network environment. Our approach is based on subjective methods. It consists of the use PRTG (Paessler Router Traffic Grapher) for QoS (quality of service) data collection and Google Forms for the different users of the network MOS (Minimum Score Opinion) parameters collection. We then implement different supervised machine learning schemes using the data collected, and finally analyze their performance. We compare two classes of algorithms namely regression algorithms and classification algorithms. The Random Forest Classifier in the second class algorithm give the best results.

Keywords: quality of experience (QoE), machine learning (LM), opinion score (MOS)

1 Introduction

Recently, the development of new information technologies and digitization of companies have involved the emergence of multimedia services. However, these services and applications can offer a poor user experience due, for example, to network overload, connection unavailability or even the usage of unsuitable terminal. Otherwise, quality of experience QoE has become the ultimate measure in enterprise multimedia networks. The time of unique networks for a type of data is revoked, we are witnessing the convergence of services as well as the proliferation of multimedia applications. These so-called multimedia networks offer poor quality of experience to users due to their requirements. Thus, predicting the user experience on the offered services should make it possible to anticipate inconveniences and finally offer them a better quality of experience.

In this context, if network administrators could accurately predict or estimate dissatisfaction of users with a service, they would empower themselves to improve the corresponding services. Hence concerning the network users, we can ask the following question:

- How to use bulk data from enterprise multimedia networks to predict QoE?

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- How to use Machine Learning techniques to predict QoE in enterprise multimedia networks?
- How to study the user satisfaction rate (MOS) based on the correlation matrix to determine the input parameters?

In this work we develop a method of bulking enterprise multimedia networks users' data and use Machine Learning techniques to predict the QoE**.** Also, we study the user satisfaction rate (MOS) based on the correlation matrix to determine the input parameters. To address this issue, we propose a subjective approach based on machine learning schemes for user score opinion measurement.
In this project, our main goals are consisted of giving a learning solution predicting user needs by the mean of the MOS and a poll survey for the evaluation of the quality perceived by users. Hence, we propose an architecture compatible with the main protocols, allowing the consideration of QoE. This architecture, composed of a QoE monitoring server, QoS parameters and a database, integrates the user's point of view as the main estimated variable, the QoE.

This paper is organized as following: the second section presents the background and state of the art, in the third section we present our proposed approach for QoE prediction in an enterprise computing multimedia environment where we give our architecture compatible with the main protocols, allowing the consideration of QoE. Then, in a fourth section, we describe our analysis method based on machine learning predicting user quality of experience which take average opinion score (MOS) as input. Finally, in the fifth section, we will give our results obtained.

2 Background and state of art

Through the quality of experience, we seek to quantify user satisfaction and their impact on the continuous improvement of the services provided by the networks. Different approaches for QoE assessment in a multimedia environment exist in the literature. So, in the references [1] [2] [3] [4] [5]the authors have described the subjective and objective methods for quality of experience prediction. The first being the basis of our research, [6] [7]exploits the MOS score for the perception of the feelings of users in relation to a network service. This score [7]is defined on a scale of 1 to 5 representing respectively mediocre service to excellent service provided by a network. The second Objective methods [9] can be captured using two methods Quality of Service (QoS) technical data and cognitive systems and human physiological testing [4]. Sometimes users provide negative feedback due to their greedy nature to get more quality services mentioned in Service Level Agreement (SLA) and also due to less technical knowledge, so this is a big deal for providers to distinguish between positive and negative QoE. Sellers don't want negative feedback from user because they spend a lot of money on product development and providing service to customers, so they want positive feedback to further improve product or service quality according to their needs. The ITU [7]provides standards known as the Mean Opinion Score (MOS) for collecting subjective user responses presented in Table 1.

Table 1:Mean Opinion Score [7]

MOS	Quality	Perception
5	Excellent	Perceptible
4	Good	Perceptible
3	Acceptable	slightly boring
2	Bad	boring
1	Very bad	very boring

It is obvious that through the user experience, network administrations try to quantify the overall acceptability of a service provided [8]in order to anticipate the annoyances of its latter in order to avoid a loss of motivation among employees. However, the references [9], [10] demonstrated that there is a strong correlation between the MOS surveys and the quality of service (QoS) parameters delivered by the network. This reason pushes us to use innovative methods based on machine learning, for the determination of correlation matrices and the prediction of user experience. Machine learning then became a strategic issue for multimedia network administrators [3] [6]. Thus in the works published in [11] [3] [12] [4] the authors propose some architecture by emphasizing on the evaluation of the quality of experience in a multimedia environment based on the methods of neural networks to estimate video quality. After studying this literature, we notice that, using machine learning method to predict QoE have been applied in cellular, video and audio networks. however, they have not been implemented in enterprise multimedia computer networks.

3 QoE prediction methodologies in an enterprise multimedia network

3.1 Description of the proposed architecture

Applied to a corporate network context [13], we provide a QoS monitoring tool. Thereafter we will develop a platform based on the MOS model which will collect the feelings of the users. We will implement six simple machine learning models to predict QoE. So, we will evaluate the performance of these methods. Our model is based on subjective approaches which consists in measuring the feelings of users by the mean of the QoS parameters and the Average Opinion Score (MOS). These parameters will be correlated through a database for the QoE prediction. Our goal here is to collect a set of subjective data that brings together several factors.

The figure 1 gived below present the architecture of the system we design for QoE prediction. It integrated various dedicated tools and software for controlling the test environment. The different components of the architecture are presented here. It consists of the following applications:

- PRTG network monitor, tools for monitoring QoS parameters in the test environment,
- Python module,
- dataset with format CSV file,
- the survey for users perceived satisfactions.

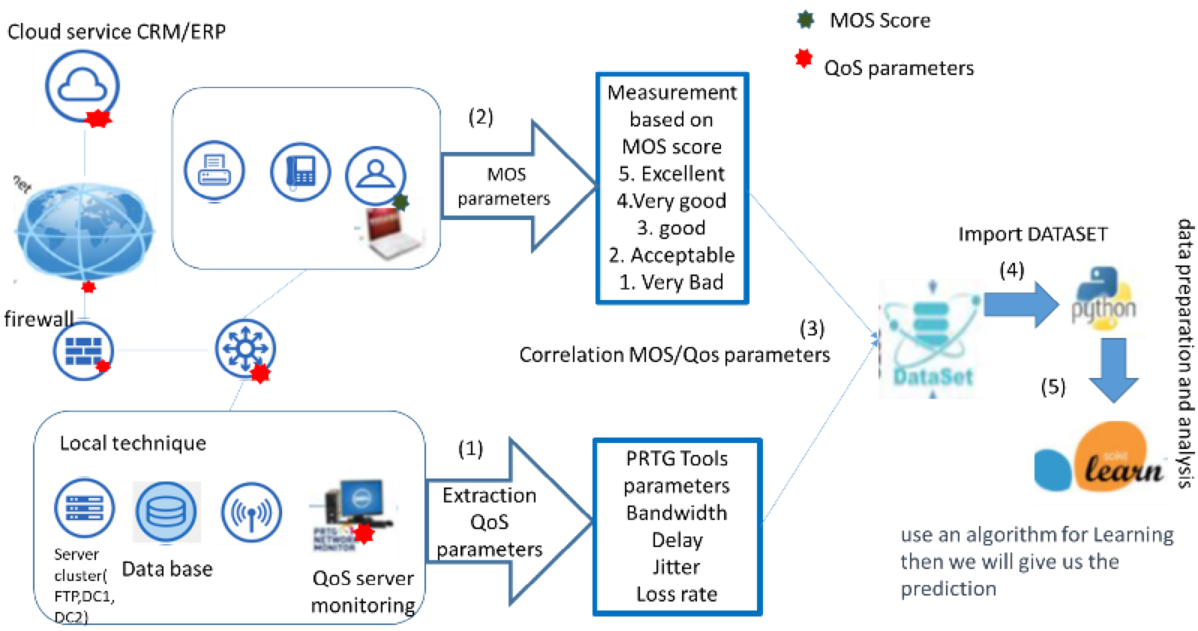


Figure 1: proposed architecture

Our approach architecture work in 5 phases:

(1) extraction QoS parameters: this phase consists of extracting network QoS parameters from the QoS PRTG monitoring tool
(2) MOS parameters: this phase consists of the recovery of MOS data from surveys for the evaluation of the feelings of users of services and multimedia applications of the corporate computer network
(3) Correlation MOS/QoS parameters: we process the two collected parameters to form a dataset in CSV format.
(4) Import Dataset: then we import our dataset into python which is our programming language that will be used for processing and analysis
(5) Data preparation and analysis: in the end we will use stick learn, the incredible machine learning library for our predictions

3.2 MOS collection

To carry out our crowdsourcing test campaign, we used the Google Forms tool. Developed by the company Google, the Google Forms tool is a solution dedicated to companies and individuals who wish to carry out online surveys to collect information. This application allows you to create forms, then collect data for analysis. This aims to collect factors and user feedback in terms of MOS scores.

3.3 Description of the dataset

The dataset consists of 5 explanatory variables describing the QoS parameters (RTT, latency, jitter, bandwidth, loss rate) and a target variable or the predicted MOS variable. We have 25 observations that trace the history of network users and their appreciation of the services provided. We seek to model a qualitative variable called QoE using a set of qualitative explanatory variables of QoS and to determine the possible interaction relationships between these explanatory variables.

3.4 Testing with learning machine

Our methodology is illustrated by the figure 3 and is based on 4 steps. The first step consists of importing the data set in CSV (common separate virgule) format into python, the second step hold for data preparation and analysis (visualization, interpretation, cleaning, correlation matrix, etc.). In the third step, we will train our algorithm for the prediction by splitting it into test data and training data. Then we will use an algorithm for learning. Step 4 will give us the prediction, then an evaluation of the method.

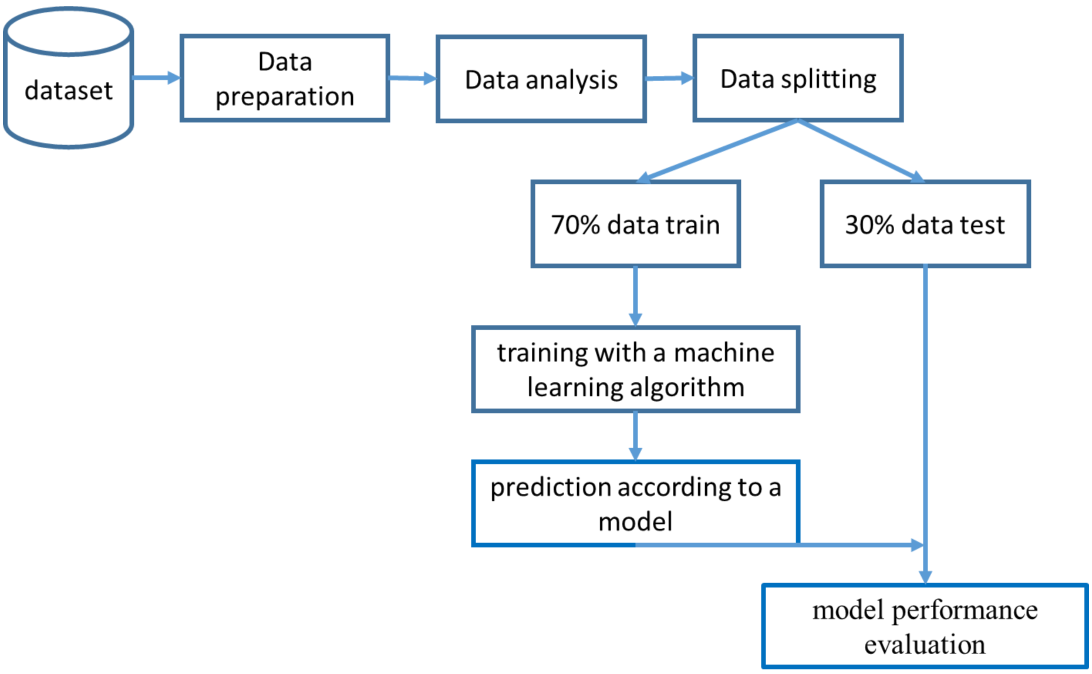


Figure 2: Machine Learning test diagram

3.5 Machine learning algorithms

Machine learning algorithms are described as learning a target function (f) that best maps input variables (X) to an output variable (Y): Y = f(X).

This is a general learning task where we would like to make predictions in the future (Y) from new examples of input variables (X). We don't know what the function (f) looks like or its form. If we did, we would be using it directly and not needing to learn it from data using machine learning algorithms.

The most common type of machine learning is learning the mapping Y = f(X) to make predictions of Y for the new X. This is called predictive modeling or predictive analytics and our goal is to make the most accurate predictions possible. In this paper, we used linear regression and classification algorithms for our prediction model. The different algorithm we have implemented are summarized in table 3. The first column presents the machine learning methods, the second column gives the algorithms. in the third column, we describe by mathematics models and last column gives the performance metrics.

Table 2: summary of methods and machine learning algorithms implemented *[1]*

methods	algorithm	modelisation	Performance
Linear methods	Linear regression	y=ax+b	R2 RSME
	Logistic regression	P(Y) ln P/1-P	
Classification	Random forest classifier	Random forest = tree bagging + feature sampling.	Accuracy Precision Recall F1-score
	Machine vector distance	y=h(x)	
	Decision tree classifier	$(X, Y) = (x_1, x_2, x_3, ..., x_k, Y)$	
	MLP Multi-layer Perceptron classifier	$f(\cdot): R^m \rightarrow R^o$	

Table (2) summarizes the different performance evaluation criteria of the algorithms used. It gives the algorithm, criteria and description of each criteria.

Table 3*:* description of the performance criteria *[3]*

Algorithm	Criteria	Description
Regression	R2	It is the proportion of the variance of a dependent variable that is explained by one or more independent variables in the regression model.
	RSME	Frequently measures differences between values predicted by a model or estimator and observed values.
Classification	Accuracy	It measures the rate of correct predictions for all individuals.
	Precision	It allows to know the number of positive predictions well made.
	Recall	The recall makes it possible to know the percentage of positives well predicted.
	F1-score	Summarizes precision and recall values into a single metric.

4 Implementation of the methodology

4.1 Presentation of the tools used

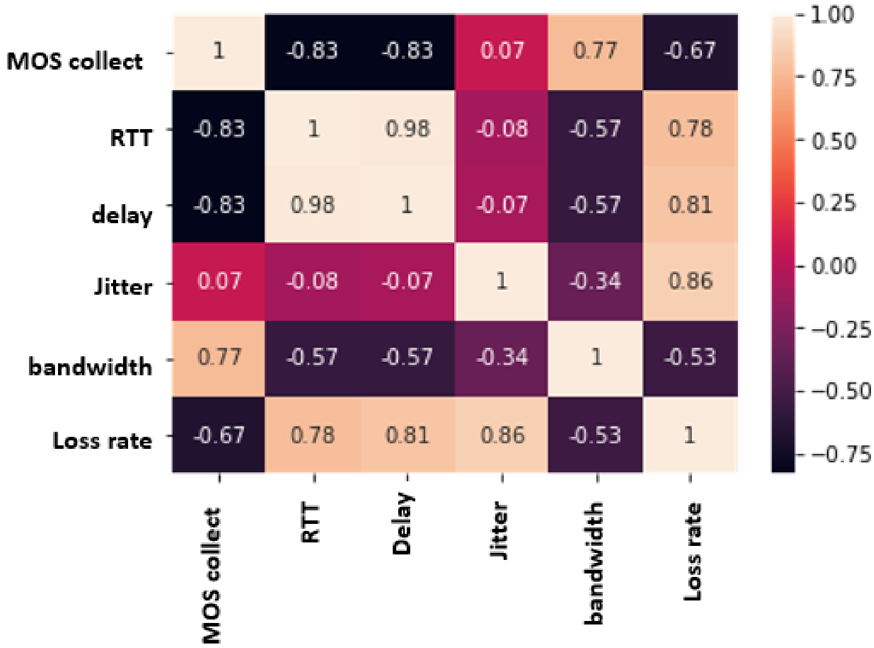
We first used the PRTG software with the QoS sensor and google Forms to collect the QoS parameters (bandwidth, availability, latency, jitter) and the MOS score. Then, in a second step, python software with its various libraries as anaconda, Matplotlib, Penda, Jupyter, Numpy, and stick Lean for data processing and analysis.

4.2 Justification of input parameters

We justify our input parameters for the prediction by a correlation matrix. This matrix highlights the QoS parameters that have a strong correlation with the harvested MOS. Table 4 present the correlation matrix of the QoS and MOS parameters. It describes how the QoS parameters impact de MOS. Before creating our model, we realize that we have 5 explanatory variables for the QoE. What are the variables that have a strong linear relationship with the "MOS" variable? To answer these questions, we make the correlation matrix. The correlation coefficients are in the interval [-1.1]:

- if the coefficient is close to 1, there is a strong positive correlation
- if the coefficient is close to -1, there is a strong negative correlation
- if the coefficient is close to 0 in absolute value, there is a weak correlation.

Table 4: correlation matrix



Through the results in the Table 4, we make the following observations:

- bandwidth and MOS collect have a positive correlation
- latency and RTT have a strong negative correlation

5 Results and interpretations

5.1 Predicted values

Table 5 presents the results of de predicted values based on the machine learning algorithms that we used. The first and second column present the different methods and algorithms used. The third column presents the MOS values collected through the survey and the last describes the predicted MOS values corresponding to the QoE.

Table 5:predicted values

Methods	Algorithms	MOS values collected	MOS Values predicted
Regression	linear Regression	[4 4 4 4 4 3 4 1 2 4 2 3 1 3 1 2 3 5 4 3 5 5 4 4 4]	[4.518, 4.54, 0,73, 4.25, 2.65, 3.27, 4.53, 3.23,3.66,3.14,4,40,1.23 ………]
	Logistic régression	[4 4 4 4 4 3 4 1 2 4 2 3 1 3 1 2 3 5 4 3 5 5 4 4 4]	[-0.00127586, -0.00036955, -0.0014048, 0.00158676, 0.00229646]
Classification	Support Vector Machine	[4 4 4 4 4 3 4 1 2 4 2 3 1 3 1 2 3 5 4 3 5 5 4 4 4]	[2 4 4 4 4 4 4]
	Random forest classifier	[4 4 4 4 4 3 4 1 2 4 2 3 1 3 1 2 3 5 4 3 5 5 4 4 4]	[3.55, 3.59, 3.57, 4.39,4.87, 2.96,4.12, 0.46,2.42,4.3,1.29……]

5.2 Regression methods

In Table 6 we present the results obtained with the regression algorithms

Table 6: performances recorded with regression algorithms

Methods	algorithm	Performance on test prediction	
Regression	Linear regression	R2=0.92	RMSE=1.16
	Logistic Regression	R2=-5.78	RMSE=1.94

The application of regression algorithms proves to us that linear regression is well adapted to our study, because the score R2 is closer to 1 and this means that it gives the best prediction.

5.3 Classification methods

Table 7 presents the results obtained with the classification algorithms.

Table 7: performances recorded with classification algorithms

Methods	Algorithm	Performance on test prediction

		Accuracy	Precision	recall	F1-score
Classification	Decision tree classifier	0.6	0.38	0.50	0.42
	Support vector machine	0.6	0.38	0.50	0.42
	Random forest classifier	0.8	0.88	0.75	0.75
	Multi-layer Perceptron classifier	0.43	0.15	0.15	0.15

We note that the accuracy and the F1 score for the Random Forest Classifier model is higher than for the others algorithms. We can conclude that this method is better (90%) adapted to predicting the quality of experience in a corporate network. The experimental results show that the classification models provide a better prediction. When we have a Sigle parameters of QoS, the linear regression model has the best prediction results. When we have multiple parameters the Random Forest Classifier gives the best accuracy score.

Conclusion

We have presented in this paper, a machine learning based approach for the QoE prediction in enterprise multimedia network. This approach implemented supervised learning methods namely regression and classification. We have evaluated its performances by simulation. The recorded results highlight the performance of the different machine learning algorithms. Firstly, in the class of regression algorithms, the linear model provides the highest prediction accuracy of about 90%. For the classification algorithms, we used the measurement of accuracy and the F1 score to carry out our comparison. The Random Forest Classification provides the best prediction accuracy of about 80%. In the future works, we will extend the dataset size and implement a data base for the storage of data collected. Also, we will study the QoE prediction which hybrid machine learning methods.

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