QUALITY OF EXPERIENCE MODELING OF MULTIMEDIA ON-LINE SERVICES

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Abstract: *This paper is focusing on some important aspects of QoE modeling of multimedia on-line services as influence factors and parameters, assessments and models. On the base of this survey we are going to propose a conceptual model for QoE prediction and to apply it for multimedia on-line services.*

Keywords: *quality of experience, quality of service, modeling, prediction*

ITHEA Keywords: *I.6.5. Model Development*

Introduction

During the past few decades service quality has become a major area of attention to practitioners, managers and researchers owing to its strong impact on business performance, lower costs, customer satisfaction, customer loyalty and profitability [Seth 2005].

Quality of experience (QoE) of the multimedia on-line services is a subjective measure which depends on a variety of factors as network quality of service (QoS), users' experience, interest and expectations, cognitive and behavioural states, costs, etc. [Mitra 2018]. The term QoS refers to the ability of the network to achieve a more deterministic behaviour, so data can be transported with a minimum packet loss, delay and maximum bandwidth but QoS does not consider the user's perception [Alreshoodi 2013]. Obviously, the QoS is a key factor for the QoE.

QoE is a multidisciplinary and a multidimensional concept. We may outline the following main challenges to investigate and predict the QoE:

- To build a **conceptual model**, including a variety of interrelated parameters with nonlinear relations;
- To use relevant **methods** for modeling in order to apply the model for QoE measuring and prediction;
- The model should be applicable in a dynamic environment for a **long time period.**

The aim of this paper is to focus on the following important aspects of QoE modeling of multimedia on-line services:

- QoE influence factors and parameters**;**
- QoE assessments;
- QoE models.

1. QoE influence factors and parameters

In the Qualinet White Paper on Definitions of Quality of Experience [Callet 2012], the main QoE influence factors are grouped in the following categories:

- **Human factors** (age, gender, education, background, etc.);
- **System factors** (bandwidth, security, resolution, etc.);
- **Context factors** (location, movements, costs, etc.)

Context can be static and dynamic. Static context may include user's application preferences, their security requirements and cost. Dynamic context can change in a very short period of time and it is uncertain. The timely collection and processing of context may be crucial as it may loose its accuracy. Dynamic context may include user location, velocity, network load, etc.

The QoE of the multimedia on-line services depends on many parameters which may be classified as context and additional.

The context parameters may be grouped in the following context classes [Mitra 2018]:

- User and user environment (location, social context, age, gender, background, etc.);
- Tools/device/object (design layout, resolutions, input/output methods, usability, etc.);
- Application (type, requirements);
- Network (bandwidth, delay, jitter, packet loss, protocols used, received signal strength, etc.).

The additional parameters include users' satisfaction, technology acceptance, enjoyment, efficiency, accuracy, perceived ease-of-use, etc. Studying and modelling these parameters is a challenging task.

In [Perkis 2006] the authors classified the technology and user related parameters as either quantifiable or unquantifiable. Quantifiable parameters include bandwidth, delay and jitter. Parameters such as expectation, attitude, ease-of-use are related to user and are deemed to be unquantifiable.

In reality, the **parameters are not independent** of each other. There can be inter-dependencies and non-linear relationships between them. For example, the parameter "user satisfaction" may affect the parameter "technology acceptance". In the model of Gong at al. [Gong 2009] each QoE parameter is a function (linear or ratio) of one or more QoS parameters. For example, "service integrity" is a function of "delay", "jitter" and "packet loss" ratio.

Further, some parameters may be hidden. i.e. they may not be observed directly. These parameters may be hard to measure and quantify.

QoE modelling and measurement require a combination of different kinds of parameters to determine overall QoE.

2. QoE assessments

There are two main quality assessment methodologies, namely **subjective** and **objective** assessment. The most commonly used subjective method for quality measurement is the Mean Opinion Score (MOS). MOS is standardized in the ITU-T recommendations [ITU-T Recommendation 2003], and it is defined as a numeric value going from 1 to 5 (i.e. poor to excellent). Usually user surveys are conducted to gather the subjective evaluation of a given service. A variety of demographics and context characteristics should be considered. The main drawbacks of this approach are: it is high in cost, time consuming, cannot be used in real time and lacks repeatability. These limitations have motivated the development of objective tools that predict subjective quality solely from physical characteristics.

The objective approach is based on mathematical and/or comparative techniques that generate a quantitative measure. This approach is useful for in-service quality monitoring or the design of networks/terminals, as well as in codec optimization and selection. The development, deployment, and modeling of the objective methods are difficult processes due to their large space parameters.

The objective approach is more reproducible, more predictable and more suitable for in-service usage for real-time service monitoring and adaptation, however very often it is less accurate than subjective methods.

Many of the objective methods convert the final results to the MOS scale. A combination of the objective and subjective approaches can be performed to overcome the shortcomings of each individual technique [Alreshoodi 2013].

The different parameters which define the overall QoE may be measured by different scales. E.g., the “user’s satisfaction” may be measured by the scale 1 to 5 but the “technology acceptance” may be measured by “yes/no”.

Mitra et al [Mitra 2018] proposed to use a bipolar interval scale to map users’ ratings into an interval scale. For example, a 5-point ordinal scale is calibrated in such a manner that the best alternative, for example, “excellent” is assigned a maximum value, ’1’; the worst alternative on the other hand is assigned the lowest value, ’0’. The mid-point is also used for calibration. For example, “good” is assigned a value of 0.50. This means that values lower than 0.50 are less favourable compared to values higher than 0.50. For example, a value between 0.8750 and 1 is considered to be “excellent” while a value in the range of 0 and 0.1250 is considered as “poor”. This way normalized values can be used to determine a QoE rating. Thus, a bipolar scale enables an expert to perform mathematical operations such as computing mean and standard deviation and the application of parametric statistical models.

In [Brooks 2010] the existing approaches of measuring network service quality from a user perspective are classified into three categories:

- Testing User-perceived QoS (TUQ) - e.g. MOS;
- Surveying Subjective QoE (SSQ) – e.g. questionnaires;
- Modelling Media Quality (MMQ) – e.g. perceptual evaluation of speech quality.

The first two approaches collect subjective data from users, whereas the third approach is based on objective technical measurements.

It is possible to measure and quantify the QoE and subsequently derive a mapping correlating the QoS parameters with the measured QoE metrics. A number of objective models have been devised for estimating QoE [Alreshoodi 2013]. The International Telecommunication Union (ITU) has developed a classification to standardize these models based on a focus of each model type. Generally, the objective quality assessment methodologies can be categorized into five types [Takahashi 2008]:

- Parametric packet-layer model predicts QoE from packet-header information, without handling the media signal itself. It does not look at the payload information; therefore it has difficulty in evaluating the content dependence of QoE;

- Parametric planning model takes quality planning parameters for networks and terminals as its input. This type of model requires a priori information about the system under testing;
- Media layer model predicts the QoE by analysing the media signal via HVS. However, if media signals are not available, this type of model cannot be used;
- Bit-stream model is a new concept. Its position is in between the parametric packet-layer model and the media-layer model. It derives the quality by extracting and analysing content characteristics from the coded bit-stream;
- Hybrid model is a combination of some or all of these models. It is an effective model in terms of exploiting as much information as possible to predict the QoE.

Since subjective scores and objective quality indices typically have different ranges, a meaningful mapping function is required to map the objective video quality (VQ) into the predicted subjective score (MOS). Mapping functions can be categorised into linear and non-linear. The linear mapping function can be used when both objective and subjective scores are scaled uniformly, i.e. an equal numerical difference corresponds to an equal perceived quality difference over the whole range [Korhonen 2012].

3. QoE modelling

Quality of Experience prediction models can be **intrusive** and **non-intrusive**, where intrusive models predict QoE by extracting features from the output signal, either on its own or by comparing it with the input signal while non-intrusive models rely on network and application parameters.

There are a variety of methods for modeling the QoE which may be classified into two main groups **– statistical** methods and methods based on **artificial intelligence and machine learning**.

3.1. Statistical methods

The statistical methods include linear and nonlinear regression and correlation analysis. These methods involve mathematical operations such as computing average, variance and standard deviation of users' ratings.

Khan et al. [Khan 2009] proposed a model for QoE estimation based on content clustering and linear regression. The prediction focuses mainly on video attributes and the video content type is extracted with content clustering. Linear regression is used to design an equation which calculates MOS. According to the presented result, video content type has a significant effect on QoE [Tsaregorodtseva 2019].

Fiedler, Hossfeld and Tran-Gia [Fiedler 2010] presented a quantitative mapping between QoS and QoE using their IQX hypothesis. It is based on exponential relationship between QoS and QoE parameters. The IQX hypothesis takes as an input QoS parameters such as packet loss and jitter (in the form of p-ordered ratio) to determine QoE in the form of PESQ MOS for VoIP applications. The authors show that the derived non-linear regression equation can provide an excellent mapping between QoS parameters and MOS for VoIP application. The authors also tested their hypothesis for QoE related to web browsing by considering weighted session time and delivered bandwidth.

The main drawback of IQX hypothesis is that it only considers one QoS parameter to predict the corresponding QoE value. The authors did not consider the problem of integrating additional context and QoE parameters to predict the overall QoE. [Mirta 2018]

Chen et al. [CHEN 2009] presented OneClick to measure and predict QoE regarding multimedia applications such as VoIP, video streaming and gaming. The authors developed a Possion regression equation to predict users' QoE based on user click rates. The user click rate is computed when the users click the keys on their keyboard corresponding to network QoS conditions. The experimental analysis comprised of VoIP and video streaming applications but considered only three human subjects.

Kim et al. [Kim 2008] proposed a method for QoE prediction based on a function of QoS parameters such as delay, jitter, packet loss and bandwidth. Firstly, a normalized QoS value is computed based on the linear weighted sum of QoS parameters. Once the QoS value is computed, it is then used to determine QoE on the scale of one to five based on another QoE function. However, the authors do not discuss in detail how the weights of each QoS parameters can be computed. Further, their method is limited to QoS parameters and treats each parameter independently.

The main drawback of such methods is that in case of subjective tests, the normality of collected data (users ratings) cannot be verified.

In an effort to reduce the need for subjective studies, the authors in [Agboma 2008] present a method that only relies on limited subjective testing. The viewers marked the point at which the change of quality became noticeable by using the method of limits. Discriminate Analysis (DA) was used to predict group memberships from a set of quantitative variables. The group memberships were separated by mathematical equations and then derived. The derived equations are known as discriminant functions, which are used for prediction purposes. In this study, two video parameter shave been used namely the bitrate and the frame rate for three different terminals and six types of video content. The authors explain that involving other factors related to the video content and coding parameters can maximize the user perceived quality and achieve efficient network utilization. The accuracy of the developed model validated for each terminal was Mobile phones: 76.9%, PDAs: 86.6% and Laptops: 83.9%. However, this approach suffers from a limited accuracy due to the statistical method used to build the prediction models. Moreover, no specific implementation was considered for the QoS parameters at the Network Layer [Alreshoodi 2013].

3.2. Artificial Iintelligence and Machine Learning methods

The second group of methods include decision trees, fuzzy logic, artificial neural networks, hidden Markov models, Naïve Bayes, k-Nearest Neighbours (k-NN), Random forest, etc. [Mirta 2018]. These methods are more flexible and more adaptive in a dynamical environment, with many unknowns and missing data.

An experiment for QoE prediction of video streams by 4 methods is presented in [Tsaregorodtseva 2019]. The methods are Support Vector Machines, Random Forest, Gradient Boosted Trees, and Neural Networks.

Support Vector Machines (SVM) are maximum margin classifiers. In particular, linear SVMs seek to find a hyperplane in the dataspace that separates the data into its respective classes and maximizes the distance between the data points of different classes that are closest to this separating hyperplane. For example, in the case of two classes and two-dimensional data, it consists of finding a line which separates the data into two classes, and the two vectors of different classes closest to the line are furthest away from each other (See Figure 1).

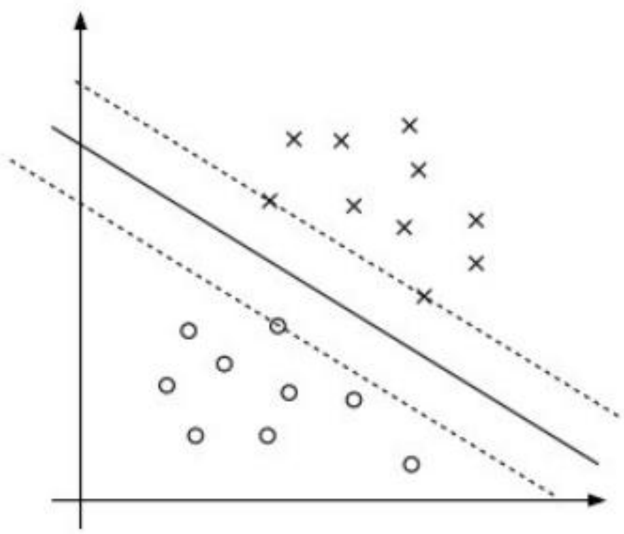

Figure 1. Linear SVM

However, most real word data sets cannot be linearly separated. The data can be projected into a higher dimensional space and the separating hyperplane can be learned in this space. A separating hyperplane can be efficiently learned with so called kernel trick – a function of two vectors k(x,y) and a measure of distance between two vectors must be specified [Scholkopf 1997].

Random forest is a supervised learning algorithm where the model is created by an ensemble of Decision Trees. A Decision Tree works by formulating a set of rules to use for prediction from the features and labels of the training data set. It can be described as a flowchart of ‘yes” or “no” questions that eventually lead to a predicted class or continuous value. Most commonly in cases of classification, the splits of nodes are chosen to maximize the reduction in Gini Impurity of their answers. Gini Impurity is a mathematical concept that represents the probability of a randomly chosen element of the set being incorrectly labeled if it was labeled by a distribution of samples in the set [Safavian 1991].

In a Decision Tree, at each node the algorithm searches through all of the possible features to find one which would result in the greatest Gini Impurity or MSE reduction, and then chooses it to split on. This splitting procedure is repeated reqursively until the tree reaches maximum depth. An issue with decision trees is that they are high variance methods and can fit noise in the dataset well, resulting in very different trees being learned for moderately different splits in the dataset. This results in severe overfitting to the training data and poor generalization performance. An approach to countering overfitting for high variance machine learning models is bagging, when an ensemble of models are trained on different random samples of the dataset. Random Forest is the application of bagging to decision trees. The algorithm selects a random subset of training data for each Decision Tree. and selects a random subset of features for splitting nodes. When a tree in a Random Forest picks a random sample of training data points they are drawn with replacement, which is known as bootstrapping, and the predictions of each tree in the random forest are averaged at test time. This procedure is known as bagging. An illustration of Random Forest with two estimators is shown in Figure 2 [Donges 2018].

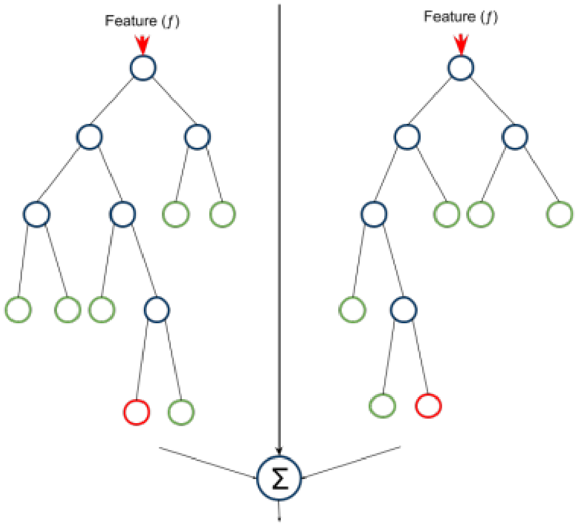

Figure 2. Random Forest with two estimators

Gradient boosting is a general technique similar to bagging that can be used to create an ensemble of models. While bagging is used to reduce overfitting of high variance models, Gradient Boosting is used to increase the power of high bias i.e. weak models that fail to fit the data well when used individually. Unlike in bagging, for Gradient Boosting the ensemble of models is trained sequentially rather than in parallel. In the case of Gradient Boosted Trees, which is the algorithm used in this work, Decision Trees are used as the weak model [Elith 2008] .

What sets Gradient Boosted Trees apart from the Random Forest algorithm is that trees are not random and independent of each other, but they are built sequentially, and each new tree attempts to minimize the loss function of all the trees combined. It is often the case that individual models in the ensemble become good at explaining data in a particular subspace of the data space and a good fit to the full dataspace can be achieved by combining of all these specialized models. Gradinet Boosted trees are quite efficient and do not use a lot of memory.

An artificial neural network (ANN), also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network.

The classical architecture of artificial neural network consists of three groups, or layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. If the signals are travelling only in one direction – from input to output layers, the network is called feedforward neural network. The input layer does not perform any computation and just passes the information to the hidden layer. The inputs have associated weights that represent their importance comparing to other inputs. Hidden layers and output layers do perform computation, and the last hidden layer's nodes pass their outputs to the output layer, which produces the final result value. Figure 3 illustrates a feedforward neural network [Upadhyay 2019]. Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point.

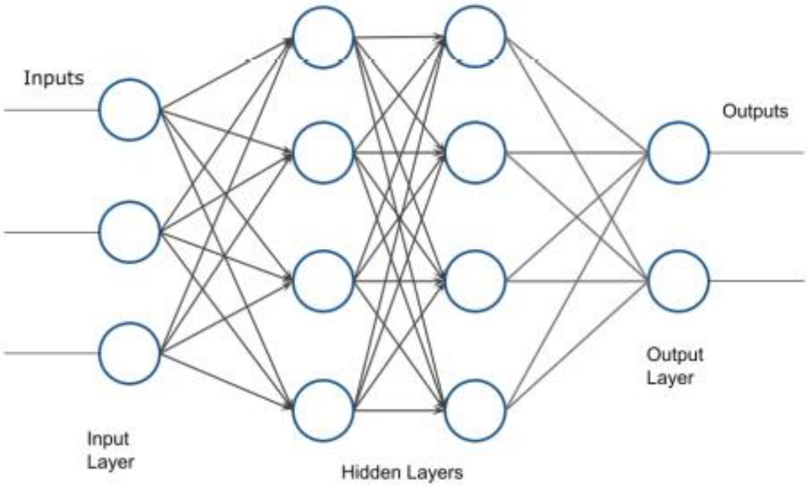

Figure 3. Feedforward Neural Network

In the standard back-propagation (BP) algorithm, the weights start off being random. Every input in the training data set is propagated through the NN, and the output is compared with the corresponding expected output. Then, based on the error, the weights are adjusted using the gradient descent optimization algorithm. This process repeats until the error is low enough, and after it terminates the NN has learned all of its weights and can be used for its intended purpose.

Artificial Neural Networks simulate the ability of the human brain for self-learning on the base of the collected information. They are used for building a self-organized architecture of the network and to define a self-learning algorithm for nonlinear systems modeling. Another important use of the ANN is in discovering theoretical links embedded in large chunks of data and the provision of richer interpretations of the interconnecting relationships existing between the variables. Since neural networks are best at identifying patterns or trends in data, they are well suited for prediction or forecasting needs.

The results in [Tsaregorodtseva 2019] show that the highest accuracy – 91.65% is achieved by Neural Networks (See Figure 4).

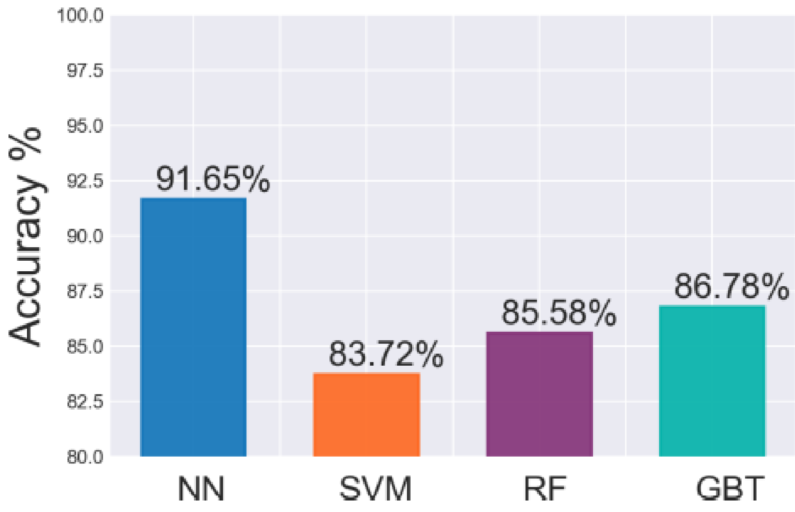

Figure 4. Accuracy of QoE prediction

Neural networks are widely used for time series prediction. They are also very suitable for modeling of the nonlinear relation between the QoE and QoS.

The study reported in [Machado 2011] proposed a method that connects the QoE metrics directly to QoS metrics according to the corresponding level of QoE. The QoE was estimated by employing a Multilayer ANN. The network QoS parameters were selected as the input layer, while the MOS, Peak Signal to Noise Ratio (PSNR) and Video Quality Metric (VQM) as the output layer. The ANN model was trained to get the correct weights. After training the ANN model, the relationship between the input layer and output layer was established. From the results, the proposed model gives acceptable prediction accuracy.

A model of QoE prediction for mobile 3D video streaming based on neural network is presented in [Almohammadi, 2019]. Neural networks are used for QoE prediction also in [Du, 2009], [Frank 2006] and many others.

Combined methods are also applied. E.g., a combined method for QoE prediction based on several Elman neural networks is presented in [Xu 2019]. Elman neural network is a type of locally recurrent network, which is considered as a special type of feedforward NN with additional memory neurons (context layer) and local feedback. As shown in Figure 5, the Elman NN consists of the context layer, input layer, hidden layer, and output layer. W^1 denotes the weight from the context layer to the hidden layer, W^2 denotes the weight from the input layer to the hidden layer, and W^3 denotes the weight from the hidden layer to the output layer. $U(t-1)$ denotes the network input vector at the $(t-1)$th iteration, $V(t)$ denotes the hidden layer output vector at the t-th iteration, and $Z(t)$ denotes the network output vector at the t-th iteration. The context layer retains the hidden layer output vector from the previous iteration; that is, $V^C(t)$ denotes the context layer output vector at the t-th iteration, and its value equals the hidden layer output vector at the $(t-1)$-th iteration. The transfer functions of the hidden layer and output layer units are $g(\cdot)$ and $h(\cdot)$, respectively.

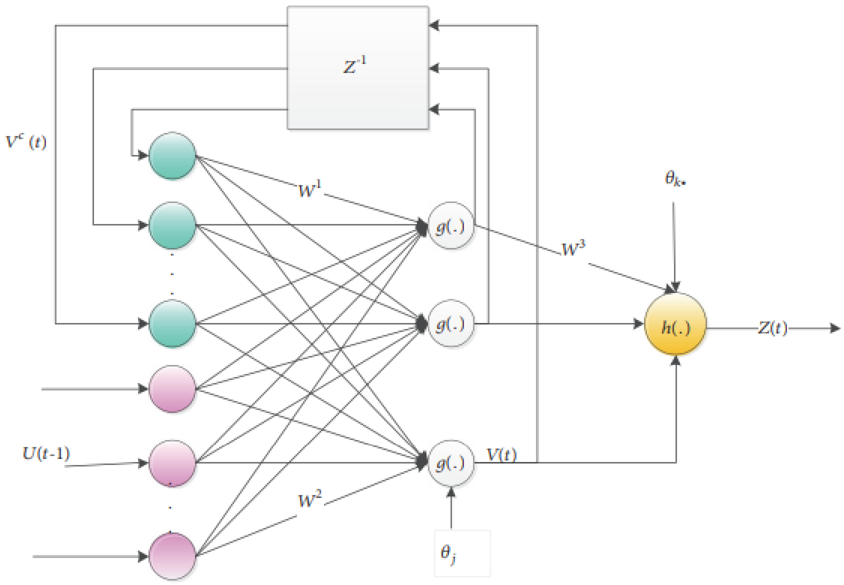

Figure 5. Elman neural network model

Because of its better learning efficiency, approximation ability, and memory ability than other neural network, the Elman NN can not only be used in time series prediction, but also in system identification and prediction. Combining the exits of the several Elman networks, the method has bigger generalizing ability and stability.

Conclusion

Modeling the quality of experience of multimedia on-line services is a complex, multidisciplinary, multidimensional and challenging task. It involves concepts from several fields as computer networks, cognitive and behavioral science, human-computer interaction, economics, etc. It includes the definition of the set of context and additional parameters and the relations between them which are usually nonlinear dependences.

Even the best modern conceptual models cannot sufficiently solve the problems of measuring and prediction of the QoE for a long time period. It is recommended to include more parameters (context and additional) as well as to apply a more systematical and unified approach. It is necessary to use a bigger data base at the entrance of the machine learning models.

On the base of this survey we are going to build a conceptual model for QoE prediction and to apply it for multimedia on-line services.

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