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QOE Prediction in Grid Based Environment

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Abstract: Distributed systems and grid environments grew up rapidly in the past few years due to increasing number of users and applicability. In the past, performance of grid based system is evaluated by using Quality of Service (QoS). The information of customer's experience with a service is being considered nowadays. QoS does not focus on the preferences of end-users of a service. To evade this issue, Quality of Experience (QoE) based on various assessment methods is used. QoE is a promising multifaceted field which is based on cognitive science, engineering science and economics, focused on the understanding of overall human quality requirements. QoE is a way of quantifying a custome's experiences with a service. This study discusses about the novel approach for QoE prediction in a grid based environment. Experimental results show that the probability based machine learning approach outperforms compared to other Machine Learning (ML) approaches.

Key words: Grid computing, load balancing, data mining, prediction, QoE

INTRODUCTION

Grid service is a software system intends to support interoperable machine-to-machine interaction over a network (Foster *et al*., 2002). Grid services are used more and more in day-to-day life for web technologies and enterprise solutions. Due to rapid growth of grid-based services, it turns out to be more important for the service providers to provide to the quality expectation of the customers.

The problem of load balancing is becoming apparent due to the popularity of high speed and distributed system. Load is the set of jobs in the waiting queue and which can be light, moderate and heavy according to their work. Load balancing is a method of improving the performance of computational grid system in such a way that all the computing nodes participate in the grid utilized equally as much as possible. Load balancing is an important operation of grid system to distribute the workload among available computing nodes to improve throughput, reduce execution time, maximize node utilization and increase overall system performance (Pandey *et al*., 2013). There are two kinds of load balancing algorithm namely, static and dynamic. In a static approach, the decision making is made in advance. In the dynamic approach, all the decisions are taken on the fly of the parameters.

There is a methodology needed to improve the quality of grid services. In the existing works, researchers attempted to increase the service quality by suitably selecting QoS parameters (such as delay, jitter, packet loss etc). Contrasting to the traditional assessment methods for quality, Contemporary research focuses on the user perceived quality. The approaches towards the existing grid services considered QoS into the account with many technical parameters. They did not consider the QoE into the account.

Quality of experience is defined by ITU as the overall acceptability of an application or service as perceived by the end user. Accurate foreseeing expectations of end users can be critical for the success of any service provider in a grid service. In today's world, migration from technology-oriented services to user-oriented services has made QoE, an essential trend and its key impact has triggered the unearthing of various QoE modeling and evaluation schemes.

There are three kinds of QoE assessment such as subjective, Objective and hybrid methods. Mean Opinion Score (MOS) is a test that is used widely in telephony networks to acquire the user's view of the quality of the network. Traditionally and implied by the word opinion in its name, MOS is a subjective measurement where listeners would sit in a "quiet room" and score the quality of calls as they perceived it. In this research, a novel

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approach is proposed to improve the quality of grid services with the help of QoE assessment using machine learning methods. Based on the nature of the grid services obtained from the machine learning model, the grid system quality is improved.

Literature review: Seppanen and Varela (2013) designed a QoE-driven network management for real time multimedia services. This solution aims to provide network-level management methods for packet traffic using QoE as a performance indicator. Experimental results show that QoE-driven management along with customer subscription scheme and traffic differentiation can make it possible to improve the perceived quality of multimedia traffic and increase the average revenue per user.

Zhai and Zhang (2010) proposed a method to estimate trustworthy of Grid services using Neural Network (NN) from the aspect of trustworthy history sequence. Experimental evaluation of their work proves that the techniques with NN are feasible and effective to estimate trustworthy of grid service.

Anouari and Abdelkrim (2014) presented a scheduling algorithm to provide QoE in WiMAX network under manhattan mobility. In this technique, if a packet loss occurs on a link in the connection then the system reduces the transmission rate of this connection to obtain its minimum allowable transmission rate. The experimental evaluation shows that the QoE provided to users is enhanced in terms of throughput, jitter, packet loss rate and delay.

Ma *et al*. (2013) proposed a QoE prediction scheme that permits a communication network to optimize resource allocation for video teleconferencing. QoE prediction problem reduces to a per-frame PSNR prediction problem with the QoE models that take the perframe PSNR time series as the input. Experimental results show that the proposed per-frame PSNR prediction method achieves an average prediction error well below 1 dB.

Staelens proposed a novel Subjective Quality Assessment (SQA) methodology based on full length movies. This methodology facilitates the assessment of audiovisual quality in the same environment and under the same conditions where users typically watch television. Experiments are conducted and compared the outcome with the results from a subjective test conducted using a standardized method. Their findings indicate significant differences in terms of impairment visibility and tolerance and highlight the importance of QoE assessment in real life scenario.

Khan *et al*. (2012) presented a new content-based and non-intrusive QoE prediction model for low bitrate and resolution (QCIF) for H.264 encoded videos and to exemplify its application in video quality adaptation over Universal Mobile Telecommunication Systems (UMTS) networks. This model is used in several other areas such as QoE control, optimization in network planning and content provisioning for network/service providers.

Even though, there is a rich literature on video and QoE measurement, our understanding of QoE in internet video is limited because of the shift from traditional methods of measuring video quality (e.g., peak signal-to-noise ratio) and user experience (e.g., opinion scores). These have been replaced by new quality metrics (e.g., rate of buffering and bitrate) and new engagement-centric measures of user experience (e.g., viewing time and number of visits) (Foster *et al*., 2002).

Balachandran *et al*. (2013) developed a predictive model of internet video QoE. They identified two key requirements for the QoE model: It has to be tied into an observable user engagement and It should be actionable to guide practical system design decisions. To evade these challenges, they presented a data-driven approach to model the metric interdependencies and their complex associations to engagement and proposed a systematic framework to identify and account for the confounding factors.

Menkovski built prediction models using traditional Machine Learning (ML) techniques based on subjective test data and explored an approach for reduction of the training dataset that would minimize the need for subjective data whilst keeping the prediction models as accurate as possible.

Bhattacharya *et al*. (2012) had done the research on an affect-based QoE evaluation framework which attempts to capture users' perception while they are engaged in voice communication. This approach consists of feature extraction from several information sources including various affective cues and different classification algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbor (kNN).

MATRIALS AND METHODS

Proposed system: Various steps followed in the proposed system are given. Hybrid QoE assessment is employed in this work. The core processes involved in this system include data collection, preprocessing, obtaining the prediction model and evaluation of the model. Firstly, the parameters which have an effect on the

Table 1: QoE parameters

Parameter	Description	Possible Values
Latency	Represents any kind of delay that happens in data communication over a network	{Low, average, high}
Bandwidth	The amount of data that can be transmitted in a fixed amount of time.	{Low, average, high}
Efficient use of Grid resources	Denotes whether Grid resources are efficiently used	{Yes, no}
Maximum load	Denotes whether the system supports maximal load	{Yes, no}
Proper load balancing	Denotes whether proper load balancing is available	{Yes, no}
MOS	Mean Opinion Score given by the user	{Poor, average, good}

quality of grid services are selected. Secondly, identification of possible range of values for each parameter is done. Then MOS value is set for each record in the data set. Thirdly, preprocessing of data is done by removing noisy data. In the fourth step, entire dataset is divided into training and test data set by using cross-validation method for obtaining prediction model. Cross-validation is done by diving a sample of data into complementary subsets, performing the analysis on one subset (which is called as training set) and validating the analysis on the other subset (called as validation set or testing set). In fifth step, evaluation of obtained prediction model is done. Parameters used in this approach are listed in Table 1.

Step 1: Choose a set of parameters that appreciably make impact on the quality of Grid service.

Step 2: For each parameter, Identify permissible range of values in accordance with the system need.

Step 3: Preprocess the data by performing data transformation and removal of noises.

Step 4: Obtain a prediction model using suitable machine learning algorithm.

Step 5: Evaluate the model using test data set and estimate the accuracy of the model.

RESULTS AND DISCUSSION

Large hadron Collider (LCG) dataset had been employed in this research which was graciously provided by the e-science Group of HEP at imperial college london. This dataset was further enhanced by the synthetic generation of the data. QoE prediction methods were applied in order to extract the forecast QoE concerning to the grid services used by the customers. The proposed work was experimented by using various machine learning algorithms and made with a comparative study. Performance of the system was evaluated by using accuracy, precision and recall. Precision is the proportion between relevant and retrieved instances. Recall is the fraction of relevant instances that are retrieved. Accuracy is the proportion of the total number of predictions that are correct. The formulae for the above mentioned measures are given:

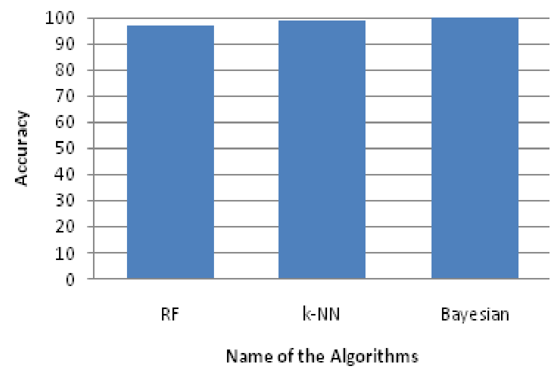

Fig. 1: Comparison of classifier algorithms against accuracy

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

where, TP TN, FP and FN are True Positive, True Negative, False Positive and False Negative, respectively. Six parameters were used for the experimentation. Number of records used in this experiment was 10,000. Experimentation was done in rapid miner tool. Well-known classifier algorithms such as Random Forest (RF), k-NN (k-Nearest Neighbor) and Bayesian Network were used in this experiment. Aforementioned algorithms were executed by using the rapid miner tool and the performances of the algorithms were compared. Comparison of the classifier algorithms against accuracy, precision and recall is illustrated in Fig. 1-3. It is observed that Bayesian Network algorithm outperforms well in terms of accuracy, precision and recall when compared to the other machine learning methods.

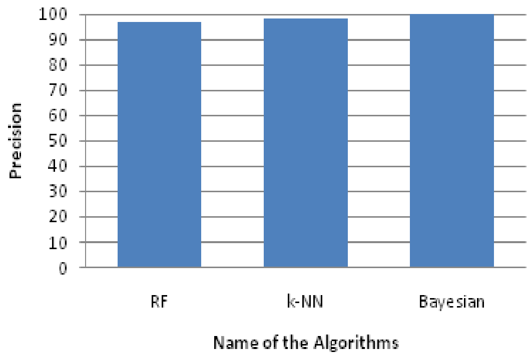

Fig. 2: Comparison of classifier algorithms against precision

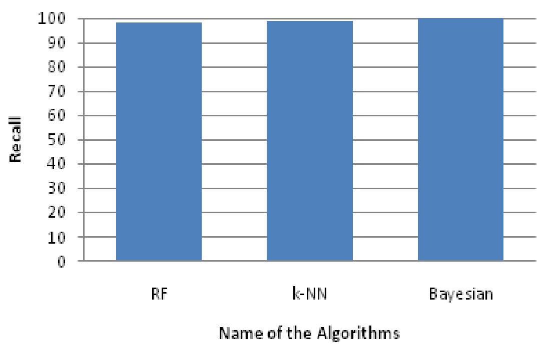

Fig. 3: Comparison of classifier algorithms against recall

CONCLUSION

Load balancing is necessary for efficient exploitation of resources and enhancing the responsiveness of a computational grid especially that hosts of services are most frequently used, (i.e., health, food and nutrition). A range of techniques have been developed and applied; each has its own limitations due to the dynamic nature of the grid. This study explores various prediction models of grid services which make use of machine learning approach. The experimental evaluation suggests that Bayesian Network approach shows good prediction accuracy than other machine learning approaches. In future, an attempt will be made to perform QoE assessment on both structured as well as unstructured data.

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