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Predicting QoE of Video Streaming with Network-Context Features

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***Abstract*—It is always the top priority for network service providers to provide better Quality of Experience (QoE). Huge efforts have been devoted to Adaptive Bit Rate (ABR) streaming, but it is only a passive QoE amelioration method by adapting to bandwidth variations. In this paper, we aim to provide a QoE prediction tool for service providers to improve QoE pro-actively. We have investigated the impacts of various network conditions on QoE through a large-scale measurement study, and proposed a QoE model from network-context features. The correlation analysis helps to figure out how the network-context features influence QoE. Furthermore, we designed a neural-network learning algorithm to predict QoE with the features of access link, location, CDN and network operators. The prediction algorithm achieves up to 85% accuracy over a large dataset of 2 billion viewing sessions from a commercial video website.**

***Keywords*—quality of experience (QoE), dynamic adap-tive streaming over HTTP (DASH), network-context features, machine learning**

I. Introduction

In the recent years, with the dramatic increase in users of online video streaming, service providers are growing more and more interests in improving quality of streaming services. There are lots of works using Adaptive Bit Rate (ABR) technique for the purpose of optimizing Quality of Experience (QoE), but they belong to passive optimization methods which only passively react to bandwidth variation. Service providers are more interested in the reason why QoE reduction occurs and how to avoid it [1]. It is necessary to propose QoE prediction tools for the service providers to help them prevent network impairment pro-actively and improve users' QoE.

Since subjective QoE is hard to measure, three categories of objective QoE metrics have been proposed: application level, network-context level and network Quality of Service (QoS) level. The application level presents objective metrics such as startup delay, bit-rate and rebuffering, which directly make impacts on QoE [2]. The network-context level includes the information of network operators, access links, location of users and content delivery network (CDN), all of which have implicit impacts on QoE [3]. Network QoS features such as packet loss and round trip time (RTT) can also affect QoE, but they are ephemeral and hard to predict [4].

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In this paper, we aim to explore the relation between application-level QoE metrics and network-context features, so as to provide QoE prediction tools for service providers to pro-actively improve users' QoE. We have carried out extensive measurement study of a commercial online video service provider for six months, and collected 2 billion viewing session logs which cover users from 60 countries and regions, 40 CDN providers and 120 different network operators around the world. We have analyzed the correlation between QoE metrics (*Startup Delay*, *Rebuffering Frequency* and *Video Quality*) and network-context information (*Access*, *Network Operator*, *Location* and *CDN*). The results unveil the insight that it is possible to improve QoE by changing network context pro-actively. Thus, we designed a neural network to learn and predict QoE from network-context information. The prediction algorithm achieves up to 85% accuracy over the large dataset.

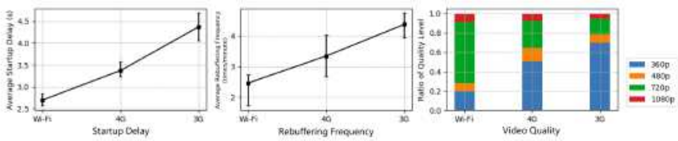
The remain of this paper is organized as follows. The measurement and data study are presented in Section II. Section III gives the design and evaluation of our QoE prediction algorithm. At last we come to the conclusions in Section IV.

II. Correlation Analysis

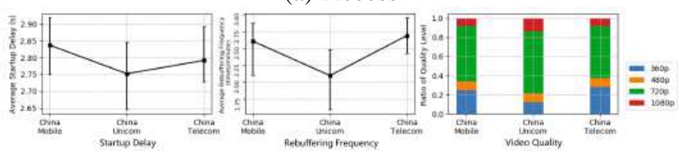
In order to reveal the relation between the network-context features and application-level QoE metrics, we have divided the samples into several categories according to the different values of features. For each category, we estimated the average of *Startup Delay* and *Rebuffering Frequency*, plotted 95% confidence interval for the estimate, and calculated the proportion of each *Video Quality* level. The results are shown in Fig. 1.

In Fig. 1(a), the samples are classified into three categories according to *Access*. The access link can influence network conditions, thus influencing the *Startup Delay* and *Rebuffering Frequency*, and leading to different client adaptation strategies which affect *Video Quality*. Having dealt with these samples, we can spot that the video sessions with *Access* of **Wi-Fi** obtain the least *Startup Delay*, the lowest *Rebuffering Frequency*, and tend to choose the videos of higher quality level, while the samples with *Access* of **3G** on the contrary.

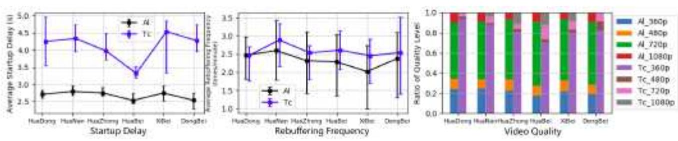
As for *Network Operator*, we choose the three largest network operators in China to analyze the differences. In Fig. 1(b), it can be found that the users of **China Unicom** are



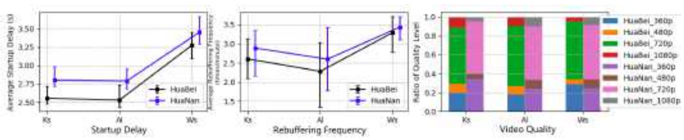
(a) Access



(b) Network Operator



(c) Location (CDN = **Al** or **Tc**)



(d) CDN (Location = **HuaBei** or **HuaNan**)

Fig. 1. Estimate of Average *Startup Delay* and *Rebuffering Frequency*, and ratio of each *Video Quality* level. For *Access* and *Network Operator*, the other features are not classified. For *CDN* and *Network Operator*, these two features and combined, with *Access* and *Network Operator* not classified.

most likely to watch online videos with higher quality, in the meanwhile, the *Startup Delay* and *Rebuffering frequency* are maintained at a relatively low level. On the other hand, the users of **China Mobile** and **China Telecom** may suffer from longer delay and more rebuffering events.

Unlike *Access* and *Network Operator*, the features *Location* and *CDN* often affect network condition as a combination, so we classify the samples basing on both the two features. The analysis reveals that only when all the combined features are specified can we precisely predict the QoE metrics.

In Fig. 1(c), the samples are located in 6 specific regions in China, with *CDN* labeled as **Al** or **Tc** according to the abbreviations of company names. As these figures show, the users of **Al** commonly have better experience during watching time than those of **Tc** judging by all the QoE metrics. When only consider **Tc** users, we may conclude that users living in **HuaBei** experience less *Startup Delay* than the other ones. But by observing the results of feature combination, it can be spotted that the users located in **Dongbei** who use **Al** are certainly enjoying the least *Startup Delay*.

Fig. 1(d) contains samples of 3 different *CDN*, with *Location* fixed to **HuaBei** or **HuaNan**. It reveals that the users of **Ws** tend to experience longer delay and encounter rebuffering events more frequently, especially those located in **HuaNan**. In contrast, the users of **Ks** and **Al** share similar *Startup Delay*, while **Al** users obtain the lowest *Rebuffering Frequency* among those of the listed *CDN*.

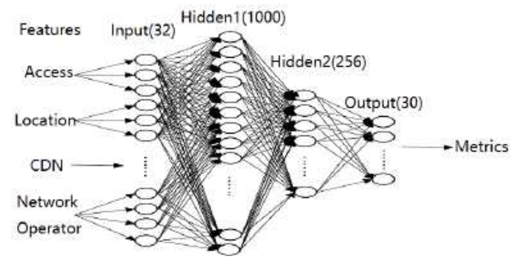


Fig. 2. Structure of neural network.

TABLE I. PREDICTION ACCURACY

Metrics	Startup Delay	Rebuffering Frequency	Video Quality	Overall
Accuracy	87.76%	86.37%	85.15%	84.83%

III. SCHEME DESIGN AND EVALUATION

To handle the relation between the network-context features and QoE metrics more precisely, we choose Artificial Neural Network (ANN) as the base architecture of our prediction model. The structure is shown in Fig. 2. The chosen features have been encoded into a 32-dimensional binary vector, and the QoE metrics are represented as a 30-dimensional binary vector. By using Backpropagation (BP) algorithm, the model processes the QoE measurement samples in sequence, calculates the gradients, and updates the weights of connections between neurons.

We randomly selected 50 million samples from the dataset and evaluated our machine learning based prediction model with the standard 10-fold cross-validation. In Table I, we listed the prediction accuracy of each metric, and the overall accuracy based on the whole dataset. The prediction of *Video Quality* is less accurate than the other metrics since some of the quality level decisions are not so suitable for the network condition owing to the lack of robust adaptation strategy on the client. The validation results show that our prediction scheme achieves up to 85% accuracy.

IV. CONCLUSION

In this paper, we analyzed the correlation between 4 network-context features and 3 QoE metrics, and proposed a QoE prediction model which achieves up to 85% accuracy. With the application of our scheme, the providers of online video streaming service can easily detect the features resulting in QoE fluctuation, predict QoE in time and adopt appropriate optimization strategies with reference to the prediction results.

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