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Data-driven QoE prediction for IPTV service

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ABSTRACT

With the development of Internet and multimedia technology, more and more families enjoy smart multimedia services provided by Internet Protocol TV (IPTV). It is crucial for operators and content service providers to find key indicators and improve quality of experience(QoE) for users. In this paper, we propose data-driven QoE prediction for IPTV service. Specifically, we define QoE to evaluate user experience of IPTV in data-driven approach at first. Then we analyze user's interests and device indicators to understand when and how they affect user experience. Based on user interest lists for both regular users and new users, we propose the *uindex* to quantify user's interests in Live TV. Finally, we build a personal QoE model based on an artificial neural network (ANN). Experimental results show that *uindex* improves the integrity of QoE description. Moreover, the model can predict QoE with an accuracy of 83.93% for regular users and 83.90% for new users in the record level, better than those of competing algorithms.

1. Introduction

With the rapid development of video services, more and more telecommunication operators are interested in providing high quality service to attract customers to subscribe. Many service providers and network operators measure user satisfaction by quality of service (QoS) which can only indicate the conditions of network performance. However, when users evaluate the provided video service, they also consider price, quality of content, ease of use and so on.

Quality of Experience (QoE) is proposed to evaluate the provided service from the aspects of human perception. ITU-T defines QoE as: "overall acceptability of an application or service, as perceived subjectively by the end user" [1]. QoS only assures the quality of the video in network level. Compared with QoS, QoE is the way to evaluate video quality from the user's perspective or user level. It can help network operators and content providers to find the way to provide better services for customers. There are also many papers to discuss the relationship between QoS and QoE [2–4]. The approaches for evaluating QoE can be categorized into three classes: subjective test, objective quality model and data-driven analysis [5].

Subjective test estimates user experience directly from users by questionnaire [6–8]. However, the drawbacks of subjective test are obvious: high cost, limited assessors and inapplicability for online QoE estimation. Objective quality models fit QoE by using mathematical tools. Most of objective quality models are based on Human Visual System or reference-based classification methods. In [9], a QoE model based on decision tree is proposed to predict user's acceptability and pleasantness. In [10], the authors use Weber-Fechner Law to describe the relationship between QoS and QoE. There are two drawbacks in objective quality model: Firstly, objective quality model is built in special scenarios. Its generalization ability is poor. Secondly, objective quality model always only considers one aspect of factors which affect QoE such as human visual or psychological factors. Therefore, it may encounter challenges when used in 5G [11–13] and wireless sensor network [14–18].

Data-driven analysis emerges for evaluation of QoE with large-scale applications of online video service. The data-driven approaches measure user experience in some quantifiable metrics which can be readily applied to real-world conditions. Many researchers focus on user behavior in large-scale measurement studies [19–23]. In [24], the authors propose a QoE model based on linear regression with QoS metrics. In [25], the authors find the relationship between network quality metrics and QoE. Then regression tree is built to predict QoE. Moreover, artificial neural networks (ANN) have been recently studied in predicting user QoE in data-driven approaches. In [26], back propagation neural network (BPNN) is used to build three-level quantitative QoE evaluation model. The results suggest that the BPNN model gets higher correlation coefficients than the linear regression. In [27], the authors build multilayer perceptron (MLP) neural network with real data from high-speed packet access (HSPA) network. They also discuss the

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influence of some key performance indicators on QoE such as average user throughput or number of active users. In [28], the authors use the nPerf to get network parameters and network assessment tool to get QoE. Finally, they build a two-layer-forward neural network to predict QoE.

However, the schemes mentioned above have several limitations. Firstly, they hardly consider user's interests in IPTV system. Secondly, QoE models based on ANN are always processed for small-scale datasets which can not take full advantage of non-linear fitting capacity. Thirdly, the researchers mostly use the basic ANN models. They hardly consider accessory technologies such as regularization, cost-function optimization and weight initialization.

Different from the existing works, we obtain dataset which contains QoS metrics associated with 1 million users from China Telecom operators. Firstly, we give the definition of QoE in IPTV for multimedia service providers and analyze the influence of different parameters on QoE. Then we propose an improved personal QoE model based on ANN with fine tuning hyper-parameters. The personal QoE model can be applied in various scenarios such as mobile social network [29–31], media cloud [32–34], device-to-device [35,36] and CDN [37].

The rest of this paper is organized as follows: In Section 2, we introduce the ways to collect dataset and define QoE in IPTV. In Section 3, we analyze the influence of different parameters on QoE. In Section 4 we propose a personal QoE model based on ANN and fine tune the hyper-parameters in ANN for predicting QoE. Then we provide and discuss experimental results. In Section 5, we give the conclusion.

2. Data collection and definition of QoE

2.1. Data collection

The process of data collection is shown in Fig. 1. For influence indicators, they are originated from four aspects: network related data, device related data, channel related data and user complaint data. The first three types of data are collected by IPTV set-top box. Specifically, network-related data such as jitter and delay are extracted by libpcap from data packets. Device related data are collected by system monitoring modules. Channel related data such as collect_time, start_time, end_time and channel_id are obtained from VOD server. All these data are updated to database from IPTV set-top box. For user complaint data, it can be easily obtained by the consumer service departments. All data collected in this paper are shown in Table 1.

Fig. 2 shows a typical session in IPTV. A user firstly opens TV and starts a session by watching a first channel. Then he tunes the channel or chooses video in VOD until IPTV is closed. In this paper, when the user changes the channel or video, we define that he finishes a prior view and starts a new view. When the user closes TV, we define that he finishes a session. For example, in this figure, the user has finished two sessions. The first session contains 6 views and second session contains 3 views.

In our dataset, service types can be split into three types: Live TV, Video on Demand(VOD) and time-shift TV(TS TV). Live TV distributes the same content for different users by multicasting, which is similar to traditional TV. VOD can allow users to select the video content from the video library provided by operators. TS TV allows users to watch TV shows after original television broadcast.

Table 1
Data attributes.

Type	Attribute	Meanings
network related data	MLR	The loss rate of media package
	DF	The Media stream delay
	JITTER	The jitter of the network
channel related data	COLLECT_TIME	The start time of one record
	START_TIME	The start time of one channel
	END-TIME	The end time of one channel
	CHANNEL_TYPE	The service type of channel
	CHANNEL_ID	The ID of channel
user complaint data	COMPLAINT TIME	The time that user make a complaint by phone call
	COMPLAINT	The complaint from user
device related data	CPU_USAGE	The usage of GPU in IPTV set-top box

2.2. Data preprocessing

When we collect large-scale data, we begin to clean erroneous data and label data.

2.2.1. Cleaning erroneous data and useless data

In the dataset, there are three kinds of erroneous data: missing data, anomalous data and duplicated data. Missing data mean the loss in attributes. Anomalous data mean values of attributes are beyond normal range. Duplicated data mean the same data in the dataset, which will lead to overfitting and resource consuming. After finding these erroneous data, we delete them.

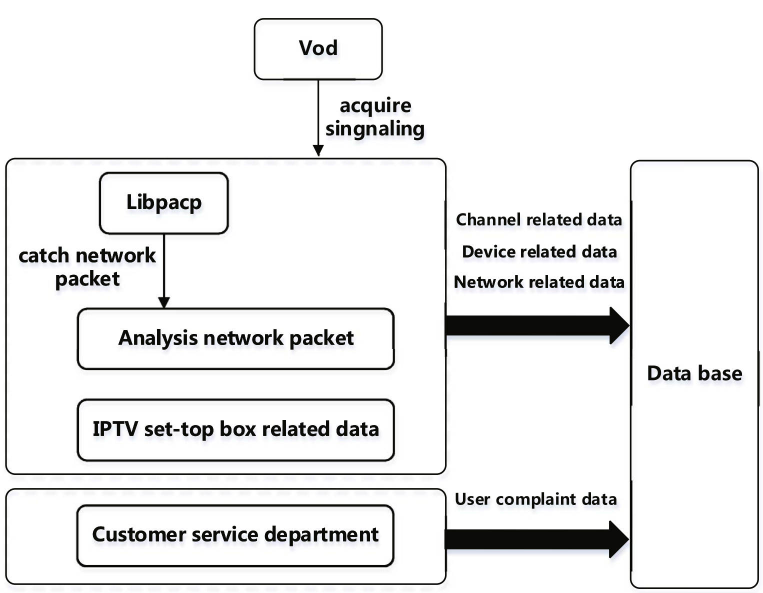

Fig. 1. The process of data collection.