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Personalized user engagement modeling for mobile videos

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ABSTRACT

The ever-increasing mobile video services and users' demand for better video quality have boosted research into the video Quality-of-Experience. Recently, the concept of Quality-of-Experience has evolved to *Quality-of-Engagement*, a more actionable metric to evaluate users' engagement to the video services and directly relate to the service providers' revenue model. Existing works on user engagement mostly adopt uniform models to quantify the engagement level of all users, overlooking the essential distinction of individual users. In this paper, we first conduct a large-scale measurement study on a real-world data set to demonstrate the dramatic discrepancy in user engagement, which implies that a uniform model is not expressive enough to characterize the distinctive engagement pattern of each user. To address this problem, we propose PE, a personalized user engagement model for mobile videos, which, for the first time, addresses the user diversity in the engagement modeling. Evaluation results on a real-world data set show that our system significantly outperforms the uniform engagement models, with a 19.14% performance gain.

1. Introduction

The increasing prevalence of mobile devices has triggered an exponential growth in mobile video services. It is estimated that, by the end of 2018, mobile video will account for over two-thirds of the world's mobile data traffic [1]. In the wake of the development of screen size and computation power of mobile devices, users have a higher demand on the viewing experience. To cater for such needs, it is essential to accurately assess video quality.

The assessment of video quality has been widely studied by the multimedia community for a long time. Pioneer researchers have tried to quantify and improve users' viewing experience by optimizing quality-of-service (QoS) parameters [2–5]. Although such QoS parameters are objective and easy to measure, their relationships to users' viewing experience are hard to quantify. To evaluate video viewing experience from the user's perspective, the concept of Quality-of-Experience has been proposed. A plethora of works try to solicit users' opinion evaluation score by conducting subjective tests [6–9]. However, such subjective tests inevitably involve lots of human participation, thus are often in small scale due to the high cost.

In recent years, the concept of Quality-of-Experience has involved to *Quality-of-Engagement*. The user engagement, compared with the subjective and hard-to-measure user perceptual experience, is a more actionable metric to evaluate user's satisfaction with the video service and directly related to the service providers' revenue model [10]. As various parties are involved in the video service ecosystem, the user engagement can be evaluated from different angles. As a pioneer, Dobrian et al. collected a large-scale data set via client-side instrumentation and investigated how the video quality parameters affect the user engagement from the content provider's perspective [11]. The authors in [12,13] developed a decision-tree-based engagement model to quantify the relationship between video-delivering QoS parameters and user engagement, which can help the design of content providers. Also, the authors in [14] examined the causal relationship between video quality and viewer behavior from the perspective of content delivery network (CDN) owner, while another study utilized massive network-provider-side data to measure the impact of network dynamics on users' engagement in mobile video services [15]. Generally, these works leverage the power of machine learning and big data to reveal the complicated relationship between user engagement and confounding factors. Nevertheless, all of the existing models are built upon the entire user data set, averaging the effect of confounding factors on all users. When applied to individual

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users, such a uniform model may fail to characterize the distinctive patterns of personal user engagement.

To investigate users' differences in their engagement patterns, we collect a large-scale video streaming data set from the core network of a tier-1 cellular network in China. We first study the impact of the downlink throughput, which is an important factor from the perspective of network provider, on the user engagement in mobile video services. The result indicates that the same factor may have distinctive effects on different users. To further investigate the effect of user diversity on engagement modeling, we employ a wildly-used machine learning algorithm, *i.e.*, gradient boosted regression tree (GBRT) [16] to build a uniform user engagement model with data of all users, and individual user engagement models for selected users. Comparing individual models with the uniform model, we find that the model parameters of a specific user are considerably different from those of other users, as well as the uniform model. This implies that a uniform model is insufficient to comprehensively characterize the engagement level of individual users.

To gain a more accurate and fine-grained insight into user engagement, we need a personalized user engagement model which can comprehensively capture the user diversity. To achieve such a goal, there are several challenges: (1) The data set consists of millions of users, and building personalized engagement models for such a large user population is quite difficult. (2) The number of videos watched by each user is rather small compared with the total number of videos in the data set, insulting in a highly sparse viewing record, which makes it hard to build accurate models for each user. (3) While soliciting information from accessory data sources is a potential solution to the sparsity problem, seamless integration of the information from various data sources is a non-trivial problem.

To tackle the above challenges, in this paper, we propose PE, a personalized quality of user engagement model for mobile videos from the perspective of mobile network provider, which takes user diversity into account and thus can provide a more accurate and fine-grained modeling. PE collaboratively learns the individual model for each user via matrix factorization and exploits the side information from other data sources to alleviate the data sparsity problem. The evaluations on a real-world data set show that PE significantly outperforms state-of-the-art user engagement models with a 19.14% performance gain.

With our system, mobile network providers can gain a more accurate understanding of user engagement with their services. Such knowledge can help them better invest network resources and perform case-by-case optimization [10]. Moreover, though our current implementation serves the need of mobile network providers, PE can easily be extended to meet the requirement of other service providers, *e.g.*, video content provider and CDN owner.

Our key contributions lie in three aspects:

- Our experiment on a large-scale video streaming data set demonstrates a significant user diversity in user engagement, which implies that the uniform model is insufficient for accurate engagement modeling.
- To the best of our knowledge, we are the first to propose a personalized user engagement model for mobile videos from the perspective of mobile network operators. This model can comprehensively capture the dramatic user diversity and provide a more accurate assessment of user engagement.
- We collect a massive video-related data set from a tier-1 network operator in China and perform a thorough evaluation of our system. The experiment results indicate our system can bring a 19.14% performance gain with respect to state-of-the-art user engagement models.

The rest of this paper is organized as follows. Section 2 reviews the related work and Section 4 defines the problem scope and validates the user diversity on a real-world data set. Section 5 formulates the problem and introduces the architecture of our system and Section 6 discusses the design of our personalized user engagement model. The evaluation results are reported in Section 7. Several piratical issues and future exploration are discussed in Section 8, followed by a conclusion in Section 9.

2. Related work

Video quality assessment has long been studied in academia. Early works on this area mainly focus on objective QoS metrics, *e.g.*, video encoding rate [2,17], bitrate [18,19] or network bandwidth [20,21], and try to improve user's experience by better QoS provision. However, as the video service is highly user-centric, the practical improvement brought by these works is hard to be validated [10]. To evaluate video quality from the user perspective, many researchers have started to evaluate video quality-of-experience via subjective tests in a controlled environment [6,7,10]. The high cost and human participation in subjective tests are inevitable for such works and thus limits the scale of their experiments.

In recent years, the concept of Quality-of-Experience has evolved to the Quality-of-Engagement. The data-driven user engagement analysis for video services has been boosted by the availability of massive data traces from service providers and the fast development of big data processing techniques. Recent literature on data-driven user engagement analysis mainly focuses on understanding the influence of different factors on user engagement. In these works, user engagement is quantified from the different perspectives. For example, content providers can quantify user engagement via the viewing time ratio [11], while network service provider may employ the video download ratio [15] as a metric. These metrics also conform with the business models of subscription-based or advertisement-based video services, which is very important from the perspective of service providers. In [11], the authors studied the impact of start-up delay, rebuffer time and encoding bitrate on user engagement. As an extension, in [12,13], the authors further investigated the impact of types of video, device, and connectivity on user engagement and proposed a decision tree-based prediction model to characterize the complicated relationship between user engagement and confounding factors. In [15], Shafiq et al. studied how cellular network metrics affect the video download ratio, and predict the download ratio with a regression tree model. In [22], Jiang et al. observe that the video quality is mainly determined by a subset of critical features and propose a novel Critical Feature Analysis (CFA) system to predict video QoE by examining the QoE of similar sessions. However, these existing user engagement models only quantify the *average* engagement of all users, while user diversity in the engagement pattern has been overlooked. As a remedy, our work propose to personalize the user engagement modeling to capture the diversity of user behaviors. We believe our personalize model can serve as a complement to these works.

3. Data set

To comprehensively study the engagement behavior at a large scale, we collect a massive data set from a tier-1 cellular network provider in China [23], which contains more than 8 million users and covers a large metropolitan area in one of the biggest cities in China from August 1st, 2014 to September 2nd, 2014.

This dataset contains information from two data sources. One data source is the raw IP flow trace captured from the links between the serving GPRS support nodes (SGSN) and the gateway