Towards QoS-Aware Recommendations

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ABSTRACT

This paper suggests the concept of QoS-aware recommendations for multimedia services/applications. We propose that recommendation systems (RSs) should take into account the expected QoS with which a content can be delivered to a user, to increase the user satisfaction and retention rates. While QoS-aware (or, network-aware) recommendations have been recently proposed as a promising solution to improve network performance, the impact of this idea on real user experience has only been speculated. Our contributions in this direction are the following: (i) we reconsider the problem from the perspective of users and the RS; (ii) to support our suggestions, we conduct experiments with real users, and present initial experimental results. Our analysis demonstrates the potential of the idea: QoS-aware recommendations could be beneficial for both the users (better experience) and content providers (higher retention rates). We believe that our study can help open a future research direction.

KEYWORDS

Quality of Service, Context-aware Recommendation Systems, Multimedia content, Experiments, YouTube video service

1 INTRODUCTION

Multimedia delivery services, such as online video (e.g., YouTube, Netflix, Hulu), audio (e.g., Spotify, Deezer), live streaming for gaming (e.g., Twitch.tv), content over social media (e.g., Facebook), etc., use recommendation systems (RSs) to best satisfy the users, and/or maximize their engagement in the service or the retention rate. Recommendations are for contents that are predicted to have high probability to be selected and liked by the user. Predictions are mainly based on user interests, history, content/user similarity scores, etc. Recommendations may also take into account the context of a viewing session (e.g., location, time, type of device, user activity, environment) [2, 3, 5, 6, 27, 28, 38, 39].

However, RSs for multimedia content services are currently agnostic to the quality of service (QoS) with which the content is delivered to the user, and QoS has not been considered as a dimension of the “context”. Yet, everyday experience and numerous studies suggest that QoS has a major effect on the overall user experience (QoE) and engagement in the service [13, 16, 21, 25]. For instance, the network congestion or topology (e.g., cached content) may affect the bit-rate, the latency, and start-up delay of a video streaming, causing annoying impairments such as re-buffering or changes in bit-rates [15, 25]. Such poor QoS delivery can be detrimental for the user QoE [13, 16]. This concern is expected to be amplified in the future, as video delivery increasingly dominates network traffic, the bar for acceptable video quality is raised, and larger portions of such content must be delivered over mobile networks, which will struggle to serve all content requests in high-QoS [12, 16].

In this paper, our major contribution is twofold.

QoS-aware recommendations. We propose to explicitly take QoS (or, the specific network conditions) into account in RSs for video and multimedia content delivery. Recommending content that can be delivered with high QoS (e.g., videos cached close to users) can lead to improved user experience. For example, if two videos have similar predicted interest to a user, but current network conditions suggest that one of them would likely suffer from poor quality streaming, the RS should recommend the high-QoS video. Our claim is that the user will then enjoy the viewing more, and possibly stay longer in the service.

Some very recent works in the area of communication networks have considered the co-design of recommendation and network optimization algorithms [8, 17, 20, 23, 33, 35, 46]. Initial results are very promising for the network performance: nudging recommendations towards network-friendly content delivery can bring significant improvements to network capacity, congestion, or energy consumption. While these findings reveal a new potential, they have two shortcomings: (i) recommendation quality and user experience was a secondary goal, i.e., considered as “something not to get too distorted” while improving network performance; (ii) the impact of this (recommendation) nudging and potential (QoE) distortions is only speculated, but is not validated with real users.

Experimental study: real user trade-offs. Hence, some key questions arise: “Should one design QoS-aware recommendation algorithms that explicitly target user experience?” and “How would real users factor in QoS, content interest, and Quality of Recommendations (QoR) into their overall experience?” While the earlier toy example, with two equally interesting contents, is straightforward, less obvious tradeoffs arise in practice. For example, how should a recommender choose between a content with predicted QoS rating 3, and interest 4, and another with QoS 4 and interest 3? What about {4, 3} and {3, 5}, respectively? Should a RS favor the content of higher interest to the user or of higher QoS? And does the answer change, depending on the scenario? Unfortunately, we currently lack answers to the above questions.
This work aims to be the first step towards answering such questions, by evaluating for the first time the joint impact of recommendation algorithms and QoS with experiments with real users. We provide initial experimental results and insights on the design of QoS-aware RSs, which we believe can motivate further research and advances in the design of QoS-aware RSs. Specifically, our results are the first to provide experimental evidence that:

- Carefully nudging recommendations towards network friendly video delivery is not perceived as intrusive by users. This is a positive message for the feasibility of the recently proposed paradigm for joint network and RSs design, which can bring significant improvements in network performance.
- QoS-aware recommendations lead to a higher overall user satisfaction as well, in addition to the network benefits.
- Recommending a high-QoS video is of equal (at least) importance to recommending an interesting (for the user) video, for refraining users from abandoning a session. Hence, by taking QoS into account in recommendations, can lead to higher retention rates and revenues for the content provider.

In total, our findings suggest that QoS-aware recommendations can benefit both the users (better experience) and the RS (higher retention rate), adding to the already shown gains for the network. Moreover, we identify complex relationships between the quality of recommendations, the QoS, and the user satisfaction, which indicates that the design of QoS-aware RS is far from trivial and requires further investigation.

The remainder of the paper describes the experiments (Section 2), provides initial results and insights (Section 3), and discusses relevant issues, such as, relation to existing approaches and technical feasibility (Section 4). We conclude the paper in Section 5.

2 EXPERIMENTAL METHODOLOGY

We implemented an experimental platform to collect data from real users. The platform is built on top of the YouTube video service: it streams videos through the YouTube service, and uses the YouTube API to retrieve recommendations and related contents.

2.1 Experiment Session

We invited users to visit our platform and participate in our experiment. We first summarize here the steps of each experiment/session, and elaborate on some key steps subsequently.

Step 1 The user enters the platform and is requested to select from a list his/her preferred region.

Step 2 After selecting a region, she is redirected to a page with instructions about the experiment. There, she is asked to start the viewing session by selecting a video from a list of 20 trending (in the selected region) videos.

Step 3 When selecting a video to watch, the user is redirected to a page as shown in Fig. 1. (a) The user watches the video (for as much time as she wants). Some videos may contain rebufferings, which are artificially added to emulate a low QoS environment. (b) 5 videos are recommended to the user to watch next. (c) The user is requested to rate her viewing experience by rating 5 parameters: (i) interest in the video, (ii) satisfaction from the QoS, (iii) relevance of recommendations (QoR), (iv) overall experience (QoE), and (v) overall satisfaction from the service (video and recommendations, QoE+R).

Step 4 Each time the user selects a video from the recommendations, step 3 is repeated. The maximum number of videos to watch is 5. After the fifth video, the experiment session ends.

The information that is communicated to the users (when they enter the experimental platform) is that they are going to select, watch, and rate a series of five YouTube videos, to some of which we may artificially introduce rebuffering for the purposes of our research study. No further information is revealed to users about how we select the videos to recommend and to present with QoS impairments, to avoid biasing their selections and ratings. We also inform the users that no personal information is collected.

2.2 Experiment Setup

Region (Step 1). We offer as options a subset of the regions provided by the YouTube API [42]: we selected 7 representative regions (different continents, diverse demographics, available video data).

Initial list of videos (Step 2). For each region, we retrieve from the YouTube API the list of 50 top trending videos. We randomly select 20 of them (for the selected region) to present to the user.

QoS impairments (Step 3a). We assumed that the network could deliver a set of videos in high QoS, and all the remaining in lower
QoS. For instance, this may correspond to the case of a congested network, where some contents are stored in a cache close to the user, thus not affected by congestion. The remaining are assumed to be fetched from remote servers, with congestion-imposed impairments. As an initial effort to emulate such scenarios, we assumed for this experiment that the available bandwidth for low QoS videos is lower than the video bit-rate, and emulated 1sec. of rebuffering every 8sec. of the video. Of course, in practice the context of QoS impairments is not limited to rebuffering, but could extend to video quality levels, changes in bit-rates, etc. [15, 25]; considering more than one types of QoS impairments could be the focus in a future, more extensive study of this topic.

Choice of high-QoS videos: For the purposes of this experiment, we assumed a list of 500 videos can be delivered in high QoS (e.g., assumed to be cached); we consider a different list per region. In each list, we select to first include the top 50 trending videos in this region. Then, for each of these 50 videos, we request its 5 recommendations / related videos provided by YouTube API. From these 2500 (50 × 50) total videos, we add in the list the 450 videos with the higher number of views ("most popular"). We stress that this would not be necessarily the "optimal" caching policy (e.g., see [8, 33, 46]), but rather a first-cut effort to differentiate between high and low QoS files. Using a more sophisticated caching policy, is orthogonal to the findings of this work.

List of recommendations (Step 3b). The list of the 5 recommendations given to the user when watching a video are either (i) the original YouTube recommendations (i.e., the top 5 related videos results returned from the YouTube API), or (ii) derived from a QoS-aware recommendation algorithm. In particular, among the recently proposed algorithms, e.g., [7, 17, 20], we use the QoS-aware algorithm of [20] due to its simplicity and relevance to YouTube1. The algorithm of [20] does a breadth-first search (up to depth 2) in the related videos provided from the YouTube API. In this search, it finds the videos that are also in the (assumed) list of high-QoS videos, and recommends them; if the search finds less than 5 videos in high-QoS, then completes the list of recommendations from the initial YouTube recommendations (and places them at the bottom of the list), and if no high-QoS videos are found then it returns the original YouTube recommendations.

Collected data (Step 3c). In each experiment session we collect the following data:
- ID of watched video
- IDs of the final recommendation list (i.e., the 5 videos presented in the right side in Fig. 1), and the positions of videos in this list
- ID of the initial YouTube recommendations; these videos were not presented to the user
- IDs of videos in the (assumed) list of high-QoS videos
- Ratings of the user for Interest, QoS, QoR, QoE, QoE+R.

3 RESULTS
We conducted an experimental campaign recruiting participants through mailing lists and social media. We collected 742 samples from users in five regions (see Step 1) around the world – in Europe (Greece, France), America (Brazil, United States) and Asia (India). In the following we present some main findings from the analysis of the results. Our aim is to provide initial insights for the applicability of QoS-aware RSs (from the user and content provider perspective), the involved trade-offs, and directions that require further investigation.

Finding 1: Nudging recommendations towards high-QoS videos is not perceived as intrusive.

One important concern is that users might perceive the "nudged" recommendations as significantly "worse", and not be willing to select them. This could nullify the expected impact on both network performance and QoS-aware recommendations. For this reason, we first study whether users are willing to select the "nudged" recommendations. To quantify this, we define two metrics: (i) the hit ratio, HR: this is the ratio of high-QoS videos that users selected, over the total number of viewed videos, i.e., the "click-through" rate for the nudged videos; (ii) the recommendation ratio, RR: this is the ratio of recommended high-QoS videos over the total number of recommended videos.

In order to better understand how these metrics attempt to capture the impact of "nudging", consider the following: Say 2 out of 5 recommendations where “nudged”, i.e., 2 of the original 5 recommendations are now replaced with 2 high QoS videos (according to the scheme described earlier). If the user picked uniformly among the original 5 recommendations, then nudging could be considered non-intrusive if the click-through rate for the 2 high QoS videos remains around 40% (2 out of 5), while lower values would suggest that users tend to disregard the nudged recommendations.

Figure 2 investigates exactly this behavior. We first plot the HR (y-axis) as a function of RR (x-axis) that would be achieved if users selected each time randomly one of the 5 recommended videos, as explained earlier (blue line - "uniform"). We also plot the respective HR values observed in our experiments (yellow dashed line). For example, this plot shows that among all the sessions where only 2 out of 5 recommendations were for high-QoS videos (x = 2), the users selected one of these 2 recommendations in about 70% of the cases (y ≈ 70%).

Hence, the HR (click-through rate) for nudged videos is not just close to the uniform average (the desired behavior), but well above, regardless of the RR value (i.e., how many of the recommendations are nudged). While this might be surprising, we conjectured that the extra "gain" in HR, comes from the fact that we were placing the high QoS video(s) on the top of the recommendation list. It has been observed that users tend to favor content higher up the list, even if videos are equally interesting [45]. Hence, for a more fair comparison, we also plot the expected click-rate taking into account content position (red line - "Zipf")2. The experimental results are still very close to this more realistic YouTube-like behavior ("Zipf").

Summarizing, the above observations provide useful evidence that using a carefully designed QoS-aware RSs not would not have a negative impact on user preferences and/or the performance of the RS. This finding becomes very important, because QoS-aware RS have

1Here we would like to stress that our goal is not to investigate the performance of a certain QoS-aware recommendation algorithm (and, e.g., compare it to the YouTube RS), but the effect of nudged recommendations; hence, the choice of the QoS-aware algorithm is orthogonal to our study and to the analysis of the results in Section 3

2The probability \( p_i \) to select the content at the \( i^{th} \) position (\( i = 1, \ldots, 5 \)) follows a Zipf law \( p_i \sim \frac{1}{i^a} \) with \( a = 0.78 \) [45]
been shown to bring significant gains to the network performance, and, here, we are the first to provide experimental evidence for the feasibility (in terms of user perception/acceptance) of QoS-aware RSs.

**Finding 2: QoS-aware recommendations bring a positive impact on the overall user satisfaction from the video service.**

A user would enjoy more a high-QoS video, among two videos in which she is equally interested. However, nudging recommendations implies that we sometimes offer less interesting videos to the user, with the intent to make up for this loss with better QoS. Yet, what would be the impact of this action on the satisfaction of the user? Will the user enjoy more the “less interesting” videos?

Table 1 shows the average user ratings for the QoS, interest, QoR, and QoE among all high-QoS and low-QoS videos. We see that the impact on user perception of recommendation quality (QoR), is not significant for the nudged recommendations. Moreover, the difference on users interest in the viewed videos is negligible. This indicates that nudging recommendations towards high-QoS content, does not affect negatively the user interest for the selected content.

|                      | Low-QoS Videos | High-QoS Videos |
|----------------------|----------------|-----------------|
| QoS                  | 1.87 (±0.14)   | 4.30 (±0.11)    |
| Interest             | 3.54 (±0.16)   | 3.61 (±0.14)    |
| QoR                  | 3.60 (±0.15)   | 3.40 (±0.13)    |
| QoE                  | 2.40 (±0.20)   | 3.67 (±0.16)    |

While this is definitely promising, the more important observation is that providing QoS-aware recommendations has a very positive effect on the total user satisfaction. The results in Table 1 (i) verify our intuition (and motivation of our work) that the impact on QoS is clearly perceived by the users (cf. the large difference in average ratings for QoS), and (ii) demonstrate that the QoS is a main factor affecting the overall user experience (QoE), i.e., a low-QoS video streaming leads to poor user experience QoE. In fact, applying a chi-squared test in our data, rejects the null assumption “QoS and QoE are independent”, with certainty (i.e., with a p-value ≈ 10⁻⁵⁴).

Figure 3 presents in more detail the joint impact of interest and QoS on the user experience (QoE). A video available in low-QoS (e.g., for 1 or 2 in the y-axis) leads always to poor user experience (less than 3 stars), even when the users are very interested in the content of the video (e.g., 5 in x-axis). On the contrary, we observe that even when the users are not very interested in the video, their experience can be moderately good when the video is provided in high-QoS; cf., for example, the average QoE is higher than 3 for 2 in the x-axis (Interest) and 5 in the y-axis (QoS).

In general, the factors QoS and user interest affect very differently and in a complex (non-linear) way the QoE. For example, denoting \( x, y \) the values for interest and QoS, we observe that while \([2, 5] \) gives a much higher QoE than \([5, 2] \), an opposite trend appears between the pairs \([3, 5] \) and \([5, 3] \). We believe that the findings in Fig. 3 motivate the need for a detailed investigation of this interplay, which could further lead to better RS design.

**Finding 3: QoS is a factor of (at least) equal significance for the retention rate in video services.**

The results above indicate that QoS-aware recommendations can benefit the users. But, is it worthwhile for content providers to adjust their RS to take QoS into account? Could this benefit their services, e.g., the retention rates, as well?

We provide an initial answer to this in Fig. 4, where we present the average ratings (y-axis) for interest, QoS, and QoR (x-axis), for all video sessions (dark color bars) and for sessions after which the users abandoned the experiment (light color bars). These results can be interpreted as an analogy to the reasons that make users to leave the video service (i.e., retention). As we can see, the difference in the average QoS ratings is negligible, while the ratings for interest and QoS are around 10% − 15% lower in the abandonment sessions. This indicates that low interest in the content of the video or low quality of the video tend to affect the decision of users to continue watching videos. While this is intuitive, our results quantify the effect of each factor. Moreover, the no-impact of QoR implies that even if good recommendations are provided to a user for future sessions, she may still leave the service due to poor experience.

4. **DISCUSSION**

While our results are admittedly preliminary, and would require more extensive experimenting to become truly conclusive, we believe they already provide enough interesting evidence to make a case for QoS-aware RSs. Next, we discuss follow-up issues related to QoS-aware RSs and our experimental results.

QoS as “context”. The QoS could be considered as an extra dimension in the “context” of a user session (e.g., a user watching a YouTube video). For instance, if the user is mobile or in areas with low quality connectivity, QoS awareness could be triggered in the RS. More specifically, research in context-aware RSs is particularly timely, e.g., as indicated by the revived RecSys workshop CARS 2.0 [1] and recent related works, e.g., [3, 5, 10, 11, 28, 30, 38, 39]. The main algorithmic approaches for incorporating contextual information into rating-based RSs are pre-filtering, post-filtering, and modeling [38]. Similar approaches could be considered for the design of QoS-aware RSs. Our work provides initial insights, which can be helpful in the tuning of the pre/post-filtering algorithms, or the development of models amenable to multi-criteria optimization [18, 19, 24, 32, 36].

**User interest - QoR - QoS models.** We need to better understand how the interest (or, recommendations − QoR) and QoS jointly affect the experience of a user and the retention rate. Our results, e.g., see Fig. 3, indicate that the relation between user interest, QoS, and QoE is highly non-linear. Similar patterns can be observed in Fig. 5 the interplay of QoR, QoS, and QoE as well. Hence, previously proposed simple/linear models [14] may not be adequate, and more...

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3. For the QoR, we consider the ratings at the previous session of a video viewing, i.e., the quality of the recommendation list that included the viewed video; the other ratings are from the video session itself.

4. The last video sessions, after which the experiment ends are not taken into account, are not considered as abandonment.
sophisticated machine learning models (i.e., beyond simple regression) may be required. Also, more experimental work (e.g., through our platform or real-world A/B tests) is needed towards both modeling the user behavior and designing recommendation algorithms. Future experiments should include different types of QoS impairments as well (video quality, latency, bit-rate changes, start-up delay, etc.), whose interplay with QoR and impact on QoE (e.g., [31]) may differ from the rebuffering impairments that were considered in our initial experiments.

Literature on QoS and RSs There exist works that considered recommendation of web services [9, 34, 37, 43, 44], cloud services [14], or services at the mobile edge [40], by taking into account the QoS. Their goal is to predict the QoS, e.g., by using collaborative filtering techniques and taking into account user location [9, 37], user clusters [34], or time models [43]. Then, they inform the user about the available services and the expected QoS. However, this is different from what we propose in this work, i.e., to incorporate QoS-awareness in the RSs themselves. Moreover, we focus our work on video services, since we believe these are of more interest today, as they dominate traffic [12, 16], have stringent quality requirements [13, 16], and make mobile networks struggle in the face of congestion [12].

Technical feasibility. QoS-aware recommendations require to know the QoS with which each content can be delivered. Existing methods (see above) could predict the QoS. However, recent advances enable an easier, more accurate estimation of the QoS. As we experience a continuous convergence of content providers (CPs) and communication systems, the CP (responsible for the RS part) could readily obtain (or even measure) network condition. For example, CPs increasingly deploy their own infrastructure to bring content closer to the user, e.g., Netflix OpenConnect, Google Global Cache, or bring their equipment inside the networks through CDNs [4]. Moreover, the dividing lines between mobile network operators and CPs are becoming more blurry, due to architectural developments, such as, Multi-access Edge Computing (MEC) and RAN Sharing, where the CP can use and control a virtual slice of the network [22]. Finally, advances in protocols and technologies for cross-layer (e.g., network/application) design exist, e.g., the QUIC protocol [29], network cookies [41], in-network application security [26], further support the feasibility of a converged approach.

5 CONCLUSION
As first class citizens in the Internet ecosystem, content RSs should increasingly incorporate a number of aspects intrinsic to the way the Internet was designed. One of the fundamental aspects of the
Internet network layer is its best-effort nature, which causes QoS impairments. In this paper, we reported results on how this very foundational aspect of Internet content delivery can impact RSs. We envision that the experimental results presented in this paper are a first step towards embracing QoS into recommendations, to jointly improve the level of satisfaction of users, content providers and networks.

REFERENCES

[1] ACM. 2019. Workshop on Context-Aware Recommender Systems (CARS), in conjunction with the ACM RecSys 19 Conference. https://cars-workshop.com/

[2] Gediminas Adomavicius and Alexander Tuzhilin. 2011. Context-aware recommender systems. In Recommender systems handbook. Springer, 217–253.

[3] Tosin Agag and Thomas Tran. 2018. Context-aware Recommendation Methods. International Journal of Intelligent Systems and Applications, 9, 1 (2018), 1.

[4] Akamai. 2019. Mobile Optimization. www.akamai.com/us/en/resources/mobile-optimization.jsp (2019).

[5] Faisal M Almutairi, Nicholas D Sidiroopoulos, and George Karypis. 2017. Context-aware recommendation-based learning analytics using tensor and coupled matrix factorization. IEEE Journal of Selected Topics in Signal Processing, 11, 5 (2017), 729–741.

[6] Linas Baltrunas, Bernd Ludwig, and Francesco Ricci. 2011. Matrix factorization techniques for context awareness recommendation. In Proc. ACM RecSys. 301–304.

[7] Livia Elena Chatzieleftheriou, Merkouris Karaliopoulos, and Iordanis Koutopoulos. 2017. Caching-aware recommendations. In INFOCOM 1–9.

[8] Livia Elena Chatzieleftheriou, Merkouris Karaliopoulos, and Iordanis Koutopoulos. 2019. Jointly Optimizing Content Caching and Recommendations in Small Cell Networks. IEEE Transactions on Mobile Computing, 18, 1 (2019), 125–138.

[9] Xi Chen, Zihao Zheng, Xudong Liu, Zichang Huang, and Hailong Sun. 2013. Personalized qos-aware web service recommendation and visualization. IEEE Transactions on Services Computing, 6, 1 (2013), 35–47.

[10] Konstantina Christakopoulou. 2018. Towards Recommendation Systems with Real-World Constraints. (2018).

[11] Konstantina Christakopoulou, Jaya Kawale, and Arinda m Banerjee. 2017. Recommender system with capacity constraints. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management. ACM, 1439–1448.

[12] Cisco. 2018. Visual Networking Index: Forecast and Trends, 2017-2022.

[13] Conviva. 2015. Consumer quality report. White paper.

[14] Shuai Ding, Shalinl Yang, Youtao Zhang, Changyang Liang, and Chengyi Xua. 2014. Combining QoS prediction and customer satisfaction estimation to solve cloud service trustworthiness evaluation problems. Knowledge-Based Systems, 56 (2014), 216–225.

[15] Trinh Viet Doan, Ljubica Pajevic, and Jorg Ott. 2015. The cloud service trustworthiness evaluation problems. In Proc. ACM International Conference on E-commerce, 202–209.

[16] Ericsson. 2018. Ericsson Mobility Report. White paper.

[17] Theodoros Giannakas, Pavlos Sermpezis, and Thanasis Spanos. 2018. Show me the Cloud: Optimizing Cache-Friendly Recommendations for Sequential Content Access. In IEEE WoWMoM.

[18] Liangmin Guo, Jiajun Liang, Ying Zhu, Yonglong Luo, Liping Sun, and Xiaoyao Zheng. 2018. Collaborative filtering recommendation based on trust and emotion. Journal of Intelligent Information Systems (2018), 1–23.

[19] Mohamad Hassan and Mohamed Hamada. 2019. Evaluating the performance of a neural network-based multi-criteria recommender system. International Journal of Spatio-Temporal Data Science, 1, 1 (2019), 34–69.

[20] Savvas Kastanakis, Pavlos Sermpezis, Vassilios Kotronis, and Xenofontas Dimitropoulos. 2018. CABaReT: Leveraging Recommendation Systems for Mobile Edge Caching. In ACM SIGCOMM workshops.

[21] S Shummu oud, Ramesh K Sitaraman. 2013. Video stream quality impacts viewer behavior: inferring causality using quasi-experimental designs. Transactions on Networking 21, 6 (2013), 2001–2014.

[22] Chengchao Liang and F Richard Yu. 2018. Soft Cache Hits: Improving Performance through Recommendation and Delivery of Related Content. IEEE Journal on Selected Areas in Communications (2018).

[23] Marim Silic, Goran Delac, and Sinisa Srbicic. 2015. Prediction of atomic web services reliability for QoS-aware recommendation. IEEE Transactions on Services Computing, 8, 3 (2015), 425–438.

[24] Liqin Song and Christina Fragouli. 2018. Making recommendations bandwidth aware. IEEE Trans. Information Theory 64, 11 (2018), 7031–7050.

[25] Yongyang Qian, Yin Zhang, Xiao Ma, Han Yu, and Limei Peng. 2019. EARS: Emotion-aware recommender system based on hybrid information fusion. Information Fusion 46 (2019), 141–146.

[26] Zibin Zheng, Hao Ma, Michael R Lyu, and Irwin King. 2011. QoS-aware web service recommendation and visualization. Knowledge-Based Systems.

[27] Linyi Song and Christina Fragouli. 2018. Making recommendations bandwidth aware. IEEE Trans. Information Theory 64, 11 (2018), 7031–7050.

[28] Shangguang Wang, Yali Zhao, Lin Huang, Jimliang Xu, and Ching-hsien Hsu. 2017. QoS prediction for service recommendations in mobile edge computing. J. Parallel and Distrib. Comput. (2017).

[29] Yiannis Yiakoumis, Zacharias Kotsialos, Sudhersan Putnam, Maged Eldawy, and Ruud van de Pas. 2019. SIR: Scalable Item-based Recommendation. In Proc. ACM ISPAC.

[30] Zhibin Zheng, Hao Ma, Michael R Lyu, and Irwin King. 2011. QoS-aware web service recommendation and visualization. Knowledge-Based Systems.