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Research paper

User Behavior towards Video Content in Mobile Devices for Designing Individualistic Prefetching Algorithm

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Abstract

Prefetching content in mobile network environment are meant to shorten users perceive waiting time. Different approaches have been taken by various literatures to provide an algorithm that is able to predict user request ahead of time. A questionnaire was design and distributed to verify approaches taken by those research using new respondents. Base on the response analyzed it is found that the most important aspect that influenced user behavior towards video content is the relevancy of the topics and WiFi is the most preferred type of connections to be used to download video content. Another behavior observed is that users who are willing to watch prefetched video also tends to download a new video. The analysis also confirms that user could be categorized to heavy and light users and they behave differently during weekdays and weekends. Findings from this survey would hopefully become guidance in designing a prefetching algorithm that suited individual needs.

***Keywords**: Mobile Communication; Prefetching; Survey; Video Content*

1. Introduction

Mobile user content usages behavior is influenced by their needs, preferences and sources available. User needs and preferences in using apps in smartphones are always limited by the sources available. These sources included network bandwidth, data allowance and local storage. To overcome this limit, prefetching could be used to shorten user perceive waiting time. Research on how to predict users' preferences, when to prefetch and how much to prefetch are all related to developing a good prefetching algorithm. However, the solutions are always based on the assumption on how users will react towards certain situation and resources. It may be true to most of the users but to certain type of users, this is not the case. For instance, majority of the users maybe prefer to use a cheaper connection for downloading contents (WiFi) but some of the users didn't mind to spent if their needs are fulfilled. To capture these individual preferences, a questionnaire was designed and distributed to verify on several issues, such as the condition should a prefetching algorithm be launched, user's willingness to watch prefetched video, time spent by the user to watch video on their mobile phone and lastly the different frequency pattern of usage during weekends and weekdays. These findings could help and will used to design a prefetching algorithm that tailored to individual user as we found that, although user tends to behave in the way the previous researches' approach claimed, there are still some users that behave differently and prefetch algorithm build for majority would not be as efficient for them.

2. Literature Review

It is forecast that by 2021, video traffic will be 82 percent of all consumer Internet traffic, up from 73 percent in 2016 [1]. Delivering video content to mobile phone users will be a challenge since video content consume a lot of resources (storage, bandwidth) but mobile phones have very limited of them. Studies have been conducted to provide users with shorter waiting time and smooth content playback. One way to achieve this are through prefetching. By using prefetching, contents are already dispatching to users' devices or at least near to users' location to provide shorter perceive waiting time when user really requested the content. Good prefetching algorithm is often determined by high hit ratio which indicate that items being prefetch is consumed by user[2]–[4].In any prefetching algorithm determining content that is relevant to user have been major concern. Factors that influence user choice to request content were discussed and studied in many literatures. Friends influences were discussed in researches related to prefetching media in social network environment.
For example in [5], [6], it is reveal that social media users tend to watch video shared by close friends and family members on social media. Data allowance and WiFi connection were mentioned in several papers [7]–[9]and efforts were being poured to balance the usage between the two connections so that user will experience cheaper but reliable connection when requesting content in mobile network. As cellular data connection is relatively more expensive compared to WiFi connection, most of the prefetching algorithm applied in mobile environment would consider to prefetch only when user devices are on WiFi connection. This approach is ap-

plied because users are predicted to favor watching videos over WiFi connection since it is cheaper compared to cellular network. This behavior is observed in [10] from 1 million unique mobile devices and more than 49 million video sessions in mobile TV service in China. They conclude that user tend to stay longer when they are watching on WiFi connection instead of cellular network. Prefetching data during WiFi connections is also discussed in [11]. They design an algorithm to learn user's changing interests. They also predicted the availability of WiFi network connections and exploits the idle period of the connections to reduce the tail-energy consumption. Playback quality also influence user to stay and continue watching video in mobile devices [4], [12]. User interest is one of the major factors that being investigated in the literature related to prefetching algorithm. It is important as it will be used to predict contents that should be prefetched for a user. User interest was discussed in [13]–[15]. Mobile user also tends to view video file when they have time to kill. For examples when waiting for turns in clinic, waiting for orders in a restaurant or waiting at the airport. All this waiting will make mobile user watch movie or video clip to kill time. This reason was mentioned in [15], [16]. To determine how many video to prefetch for certain users, they are categorized into heavy and light users [14]. They correlate the number of videos to prefetch with the users past activity and conclude on the number of videos to be prefetched. Researchers also categorized prefetching into long term and short term prefetching [17]. All the inputs from these literatures are taken and used to design questions in a survey. User feedback on the matter were analyzed in section V, VI,VII and VIII to see to what degree did these factors influence and relevant to them . These factors need to be verify as most factors considered in the research are based on the majority preferences.

3. Methodology

To capture user behavior towards video contents in mobile devices, a questionnaire was designed using survey monkey tools[18] and distributed online through e-mail and social network posting. It was distributed from November 2017 to February 2018 and received 244 complete responses from 258 responses. The questionnaire contains 18 questions. Questions 1 to question 6 are question on the demographic data. The rest of the question is designed to capture user behavior while using mobile app on their devices. To capture factors that influenced user to watch video on mobile devices users was asked to state how important certain condition in influencing them to watch video online. Six conditions were listed (WiFi connection, smooth playback, time to spare, friends' influenced, data allowance and interesting topic) in the questionnaire and user was asked to rate them based on how importance are the conditions to them. To verify if users are willing to watch prefetched video, user was asked whether they willing to watch prefetch video from a trusted source. User was given a few options on what circumstances they are willing to watch prefetch video and one option if they are not willing watch it at all. Then, to confirmed if user will only watch prefetched video, a subsequent question was asked. Users' feedback on this question will prove whether it is feasible to prefetch video in mobile devices and whether immediate prefetching is needed once users start consuming video prefetched for them. To measure how much contents should be prefetched for each user, they are asked to state how long in hours they spent on video content providers' website. Lastly, to verify that user behavior is different towards content usage during weekdays and weekends, user was asked to rate how frequent they performed common activities in their mobile devices during weekdays and weekend.

4. Respondent Profile

Respondent profile was collected in the survey to ensure that respondents are coming from different academic background, vary in age range and level of work in order to avoid bias feedback. It could be observed in Table 1 that respondents are coming from varied age group, academic background and job level.

Table 1: Respondent Background

		Percentage	*Frequency*
Gender	Female	63.52%	155
	Male	36.48%	89
Age	18 to 24	18.85%	46
	25 to 34	21.72%	53
	35 to 44	40.16%	98
	45 to 54	15.57%	38
	55 to 64	3.69%	9
Qualification	Secondary school	2.46%	6
	Diploma	16.39%	40
	Foundation degree	2.87%	7
	Bachelor's degree	18.03%	44
	Post-graduate degree	60.25%	147
Job Level	Owner/Executive	6.56%	16
	Senior Management	21.72%	53
	Middle Management	29.51%	72
	Intermediate	16.39%	40
	Entry Level	6.97%	17
	Other (please specify)	18.85%	46

4. Reason to View Video File in Mobile Devices

Reasons to watch video file in mobile devices were listed in the survey and user was asked to rank them based on the priority. Video file was chosen as this file one of the most resources consumed file that is popular among mobile devices' user. These reasons are listed based on a few literatures that research on prefetching for mobile network and devices. Inspired by research approach discussed in section II, these reasons were included in the questionnaire to get feedback from user on what they considered as the most important reason impact their choice to watch video on mobile devices. User was asked to rank the reason based on their priority. Rating average is calculated to give a clear picture on which factors are the most important.

Rating average, *r* was calculated as

$$x1w1 + x2w2 + x3w3 \ldots xnwn \quad (1)$$

Where
w = weight of answer choice
x = response count for answer choice

User responds to the question is illustrated in Figure 1. User considered their interest on the video will be the most crucial factors to consider when watching video on mobile devices. WiFi connection, smooth playback and if they have time to kill contribute almost similar rating average indicate that respondents also consider them among the important reason to be considered when watching video file. To determine whether user is idle and have some time to spare, their location could be tracked and certain place always suggested that user is on a trip (airport, train station etc) or waiting for something (bus stop, clinic etc). User put their friends' interest in the video and enough data allowance as less important reason that encourage them to watch video on their mobile devices.
These findings provide an insight of what parameters that need considerations when designing an algorithm. For prefetching algorithm to perform it task, it need to know what video is relevant to users, what kind of connection the devices in connected, user next location and how user connected to their friends in social network. However, to determine to what degree these parameters is important to users', individual preference must be considered. Not every parameter is applicable for each user. Prefetching algorithm that able to predict video that match user preferences, location and

situation that convenient to users, will encourage users to watch prefetch video, hence smooth playback could be guaranteed for them.

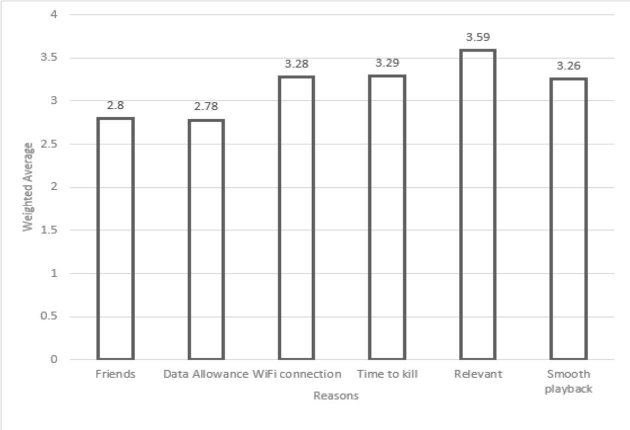

Fig 1: Reason That Influence Respondent to Watch Mobile Video**.**

5. User Willingness

It is pointless to prefetch contents if users are not keen on using them. For that reason, a question was asked if respondents are willing to watch video that are prefetch in their devices. Figure 2 illustrates users' response on the question. When asked if respondents are willing to watch videos that are prefetch for them by a trusted application, more than 90% of the respondent are open to watch the video for various reason. This prove that users are more likely to consumed content prefetch for them if the topic, situation and location suited them. For instances if the topic is relevant to them, it is more likely the content will be consumed. However about 18% of the respondent are willing to watch video simply because the content is already available for them which is quite an interesting finding. For this kind of users, perhaps less parameters could be used to determine what and when to prefetch.

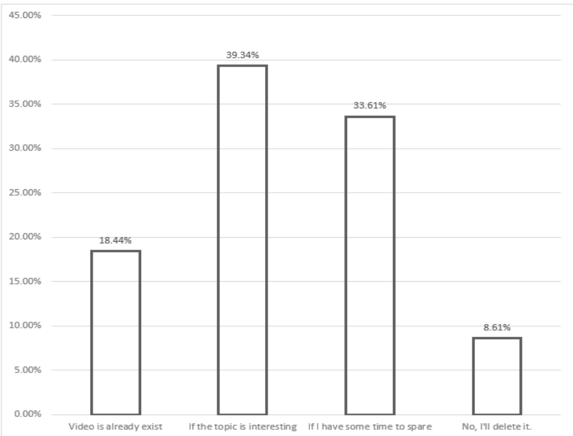

Fig 2: User Willingness to Watch a Pre-fetched Video

To emphasize on user willingness to watch prefetched video, respondents were asked whether they will download a new video using their data allowance. However, the response shows some contradiction when more than 50% of user are willing to use their data allowance (if they have enough at the time) to download a new video file. About 40% of the respondent are consistent with their choice when they refuse to download video file using their data allowance. Figure 3 illustrate the findings. Based on these findings, in can be concluded that even though users are willing to watch prefetched video, there are no guarantee that user will only watch the prefetched video. User might decide to download another video depending on video how relevant the video for them and their data allowance limit. For this situation, it is important to anticipate next video that will be watched when users are watching prefetched video especially if the user is categorized as heavy user (findings in the next section). Two phase of prefetching algorithm should be considered to tackle this situation. First phase is would be long term prefetching [17] which is to prefetch probable video that will be watch by user before it being request and second phase would be short term prefetching [17] which is to prefetch next content that related to currently viewed content .

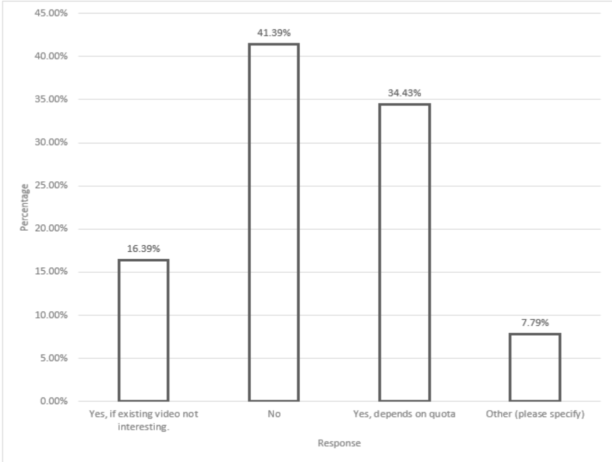

Fig 3: User Willingness to Download a New Video.

6. Duration on Video Streaming Website

To capture how long respondents, spend on video streaming website, a question requested users to state duration (in hours) that they spend on the website. Figure 4 illustrated how long users claimed they spent-on video streaming related website. This question is based on findings in [14] which state that user can be categorized into heavy and light users. Most of the respondents, which is more than 60% only spend less than one hour on video streaming website. About 24% percent spend 2 to 3 hours and the rest are spending more than 4 hours a day watching online videos. If we are to categorize user to heavy and light users, we could determine how aggressive should we prefetched to certain type of users. Light user will not appreciate if too much content is prefetch for them. In contrast, heavy user would expect more content and the lack of them will influence them to request for them in real time which will reverted the benefit of prefetching.

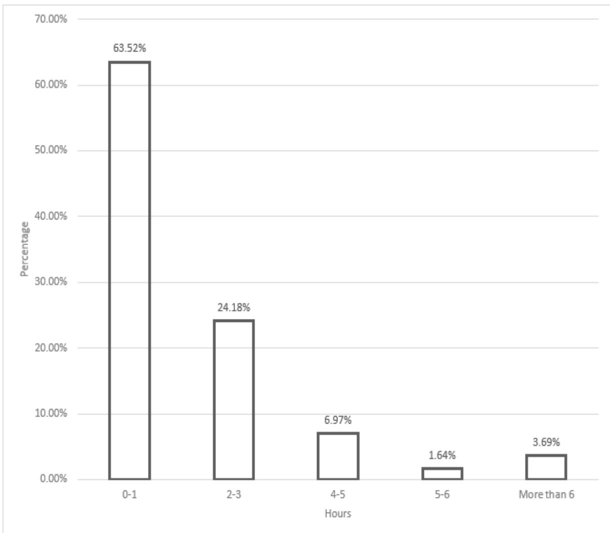

Fig 4: Duration Spends on Video Streaming Page

7. Weekdays vs. Weekends

Some researchers suggested that there are significant different activities in mobile device usage on weekend and weekdays and different prefetching policy should be applied accordingly [5]. To confirm this observation, respondents was asked to state how often they perform common activities on their mobile devices on weekdays and weekends. Figure 5 illustrated the findings. WD and WE in the chart refers to weekdays and weekend respectively and number 1 to 5 at the end of it is the frequency of the activities performed with 1 is rarely used and 5 is most often. Phone calls, emails and instants message activities weighted average are higher on weekdays compared to weekends for these activities are often related with works. In the other hand, games, online shopping, photo and video viewing and social network seems to be higher on the weekend since these activities are associated with leisure time. However, pattern between activities didn't shows any significant different as instants message is still the most popular activity during both period and similar pattern could be observed from other activities. It seems that prefetching algorithm could consider user temporal data to make sure that prefetching could be made tailored to the user needs and behavior.

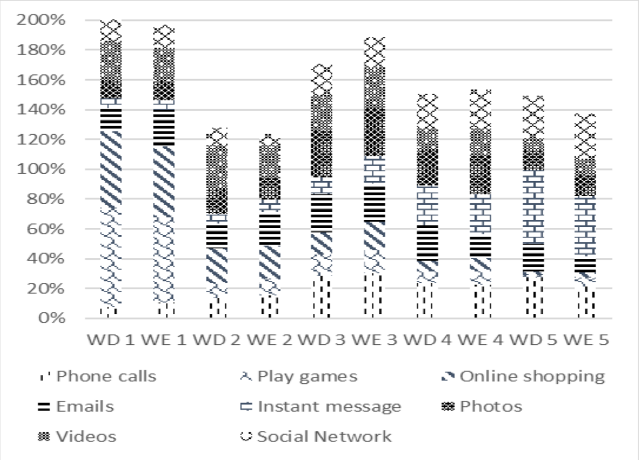

Fig 5: Weekday Activities versus Weekend Activities

8. Conclusion

Findings on the survey have reveal and confirm user behavior towards resources on their devices that crucial for content prefetching. Those findings are:

8.1 Content prefetched for user must be relevant for them. Prediction and recommendation system method could be applied.

8.2 Most of the prefetching activities should be done during WiFi connection and knowing user location and situation would be an added advantage to predict when video contents should be prefetched. User location could be used to predict the situation that they are in at the moment. (eg: working or travelling)

8.3 User that are willing to watch prefetch video are also tends to download new video. Short term prefetching mechanism could be applied for them to ensure Quality of Experience (QoE) during viewing time.

8.4 There are heavy and light users. Prefetching algorithm should prefetch according to individual preference. Prefetching too much content for light users are not necessary and resources' consuming and prefetching not enough data for heavy users will influenced them to request for them in real time which will reverted the benefit of prefetching.

8.5 Temporal data should be considered as there are different activities' frequency during weekend and weekday.

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