

Quality of Experience Measurement of YouTube Videos

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By

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DECLARATION

This is to certify that the thesis entitled “**Quality of Experience Measurement of YouTube Videos**”, submitted by me to the *Indian Institute of Technology Guwahati*, for the award of the degree of Master of Technology, is a bonafide work carried out by me under the supervision of Dr. T.Venkatesh. The content of this thesis, in full or in parts, have not been submitted to any other University or Institute for the award of any degree or diploma. I also wish to state that to the best of my knowledge and understanding nothing in this report amounts to plagiarism.

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This is to certify that the thesis entitled “**Quality of Experience Measurement of YouTube Videos**”, submitted by Rupesh Kumar Koshariya (134101041), a master’s student in the *Computer Science and Engineering, Indian Institute of Technology Guwahati*, for the award of the degree of Master of Technology, is a record of an original research work carried out by him under my supervision and guidance. The thesis has fulfilled all requirements as per the regulations of the institute and in my opinion has reached the standard needed for submission. The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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Sincerely
Rupesh Kumar Koshariya

ABSTRACT

User generated content has become very popular since the introduction of YouTube. Compared to traditional VOD services YouTube is different because it provides more control to user for content generation. Due to popularity and growth of YouTube quality monitoring of YouTube is essential and it is also important to determine the factors that influence quality of experience parameters.

In this project we are measuring quality of experience of YouTube videos by objective parameters i.e startup delay, no of rebuffering events, duration of rebuffering events. We have also conducted measurement study that compares tolerance limit of startup delay and no of interruption for users which is based on duration of videos. We have also investigated variation of tolerance limit of startup delay when the type of network changes. For this purpose data sets are collected by user computer where a chrome extension is installed in university campus network and bandwidth is throttled according to requirement.

The results shows that there is significant impact of duration of video upon QoE parameters. We have shown that as the duration of video increases users tend to be more tolerant for quality of experience parameter. In the same way users are more tolerant in WiFi network compared to LAN. The data shows that 60% of the users prefer to wait for 4 to 6 second for short duration video (less than 5 min) whereas for long duration videos (more than 1 hr) the time increases upto 7 to 9 second. Also 77% of the users can tolerate 2 or less than 2 video interruption in short duration videos whereas in long duration 59% of the users prefer to wait for 4 to 6 rebuffering events.

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Chapter 1

Introduction

After the introduction in 2005 and acquired by Google in 2006, YouTube became the most popular website, because of its unique feature of user created content. According to website popularity estimation Alexa(www.Alexa.com) , YouTube currently hold third place in global chart and fourth place in India among the most visited website. It is the most bandwidth intensive service of today's Internet [1]. According to a report 15 to 25% of all inter autonomous system traffic today is video. YouTube is a prominent source of that Internet traffic today, with everyday people watch hundred of million of hours on YouTube and generate billions of views. 300 hours of video are uploaded to YouTube every minute. YouTube has more than 1 billion users [2].According to an estimate YouTube share 60% part of total video watched on the Internet with 65000 video uploads every day [3].

1.1 YouTube Functionality

YouTube is a web based service which provides the facility of video sharing via the Internet. Clients can create their own content and upload them in YouTube. Viewers can search the videos and watch them in their computer or mobile device. YouTube is based on client server mechanism. Now a days servers are deployed for fast video delivery

service so that users can get good and efficient service. Watching a YouTube video involves different set of servers. Presently YouTube supports two containers one is flash and the other is HTML5. There are different type of file like .flv, .webm, .mp4 are supported by YouTube embedded player. At first a HTML page is downloaded in client from front end server of YouTube when video is requested. Other content like shockwave flash player are also requested once base HTML page downloading is finished. Video and audio are also requested from CDN server. If server is not able to handle request then it redirect to other server, otherwise it delivers the content. Client starts playing the video. The procedure for video delivery in YouTube are as follows:-

- User request the video either by selecting the video in website in form of small thumbnails or access directly by using video page URL.
- After selection of video an HTTP GET message is sent from client to web server of YouTube. The web server redirects the clients with HTTP 303 with server address.
- Content server name is resolved using DNS query to local DNS server. IP is obtained of server by the query.
- Finally the client request video by HTTP GET request to content server.
- The request is received and content is delivered to client.

1.2 HTTP Adaptive Streaming

Traditional Streaming protocol uses a stateful protocol where once a client is connected to streaming server, server keeps track of client's state until the communication is finished. Such functionality were used in Real Time Streaming protocol. Alternatively to this streaming protocol progressive download may be used which uses standard HTTP web server, but the drawback of this technique is that it waste bandwidth when users want to switch video and it is not bitrate adaptive as well as it does not support live streaming. The weakness of both the strategies are addressed by Dynamic Adaptive Streaming over HTTP (DASH). IN DASH media preparation process typically generate segments that

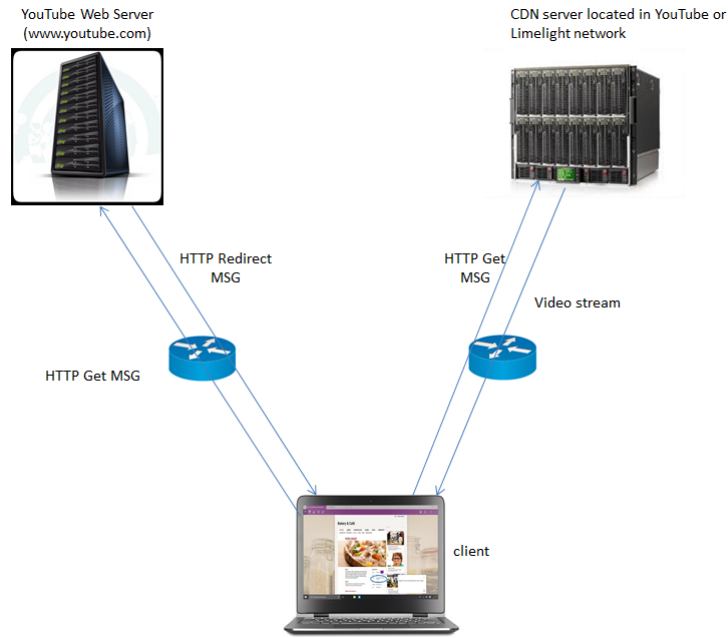


FIGURE 1.1: Video retrieval in YouTube

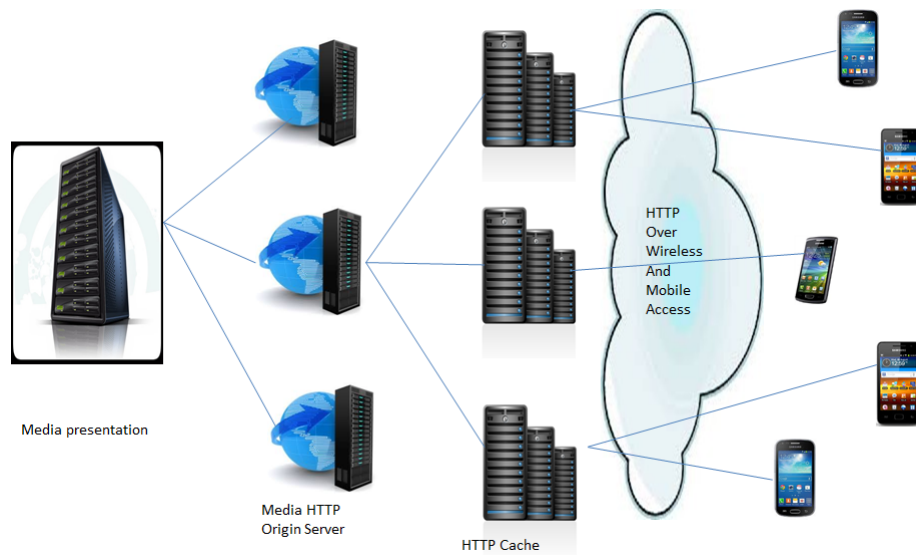


FIGURE 1.2: Example of Media Distribution Architecture

contain different encoded version of one or several media component of media content. Media Presentation Description(MPD) are hosted along with segment in origin server which are typically a HTTP server. Based on MPD metadata information client request the segment using HTTP GET method. The client is responsible for controlling streaming session and smooth streaming session.

The reason that lead to choice of HTTP as delivery protocol for streaming services are summarized below[4].

- A lot of network uses NAT and firewall which blocks some services but due to HTTP based delivery in DASH, it provide easy and effortless streaming service.
- Due to usage of HTTP and TCP/IP protocol it provide reliability and deployment simplicity.
- HTTP based delivery provides ability to move control of streaming session entirely to the client.
- DASH does not require negotiation with streaming server for initial content rate because HTTP based delivery automatically chooses initial content rate to match initial available bandwidth.
- HTTP based delivery provides smooth content rate switch on the fly on the event of bandwidth change.
- In HTTP based delivery standard HTTP server and standard HTTP caches can be used which are already deployed in the network.

1.3 Quality of Experience

With the increase in traffic, network operator and provider are interested in end user quality during video playback. This end user quality is measured by quality of experience. Quality of Experience has been defined by ITU as “ The overall acceptability of an application or service as perceived by end user subjectively”. There are plenty of factors that affect quality of experience of the user which is called influence factor. Influence factor can be defined as “ Any characteristic of a user, system, service, application or context whose actual state or setting may have influence on the quality of experience for the user ”. For example type of network, type of device, duration of video, type of content etc are included in influence factors. For estimation of quality of experience we have included following parameter in our measurement.

- **Startup Delay**-Startup delay can be defined as the response time of video player. It is an interval between the request for the content to the time when player start

playing video. There are various factors that can affect startup delay for e.g bandwidth, YouTube server selection policy, DNS load balancing, server redirection and popularity of video. If bandwidth is low it will take more time to buffer the segment before the player start playing video [5].

- **No of Rebuffering Events**-Stalls or rebuffering are the consequences of an under-run of the client buffer. This situation can arise when there is temporary mismatch between the bandwidth estimation made by client and actual bandwidth available in the network. One of the factor that is responsible for stall is cached and uncached segments. As cached segments creates the perception of high bandwidth availability which leads to incorrect estimation of bandwidth by client. The frequency of stalls is inversely proportional to QoE [6] .
- **Delay of Rebuffering Events**-The duration for which the stalls are take place is also one of the key parameter in measuring QoE. If the duration of stall are very long then user tend to pause a video so that sufficient buffering will take place and he can watch video smoothly. The other consequences can be the decrease in quality level of video or in general user tend to switch between the video or refresh the page. Like frequency of stall, delay of stall will increase if user tend to switch the quality level or seek the video.
- **Session Viewing Time**- Session viewing time is user engagement parameter. It is the fraction of video watched by the user. It is not necessarily equal to total video duration. By the help of other QoE parameter like startup delay and no of stall in association with session viewing time we can easily estimate whether the video switching has taken place due to bad QoE or due to irrelevance of the content. It also tells about how much the user is engaged to whole session of video streaming [7].

1.4 Rationale for Measuring QoE

QoE data can be used by the network operator, the CDN and content providers to monitor and manage the QoE of their network and streaming services respectively. The point is that measurement for QoE would make operator, device provider and service providers more convenient to judge and improve the service they provide for YouTube consumers.

1.5 Problem Definition

Measuring the Quality of Experience of YouTube videos and study the impact of duration video on startup delay and no of rebuffering events and impact of type of network on startup delay.

The remaining of the thesis is organized as follows. Chapter 2 describes background or related work done on this area. Chapter 3 details the methodology used for the setup of experiment, whereas chapter 4 reports the experimental results. After describing conclusion on chapter 5 we end the thesis with future work in chapter 6.

Chapter 2

Literature survey

In the field of YouTube we have divided the literature in broadly two categories. The first one is YouTube infrastructure and other one is measurement of QoE.

2.1 YouTube Infrastructure

In this category basically literature deal with YouTube traffic and CDN server. Due to this two important elements of YouTube infrastructure we have divided the work in traffic characteristics and server selection strategy.

2.1.1 Traffic Characteristics

In this category of work researcher tried to understand workload pattern so that infrastructure can be plan, design and built more efficiently. In 2007, Phillipa Gill et al. used multi level approach to measure and observe YouTube traffic locally in a campus setting as well as they examine over the most popular videos on the site. They found out that access pattern are strongly correlated with human behaviour, as traffic volume vary significantly by time of day, day of week etc. They suggested that YouTube like site where any one can publish content require decentralized approach such as caching and CDN

and metadata should be exploited efficiently [8] In 2009, Michal Zink et al. analyze the content distribution and conducted study in university campus network. They analyzed the duration and data rate of streaming session, the popularity of videos and access pattern for video clip from the client. They demonstrate that statistical information can be used to method like P2P based distribution and proxy caching can reduce network traffic significantly [9].

2.1.2 Server Selection Strategy

Researcher aimed to obtain understanding of YouTube CDN and quantify its effectiveness. They try to obtain deeper understanding of factors that impact serving of video from YouTube data center. In 2011, Ruben Torres et al. analyze from their datasets that YouTube request are directed to a preferred data center and the RTT between user and data center plays a role in video server selection process. The videos are also served from non-preferred data center due to load balancing of DNS server, variation across DNS server within network, alleviation of load hot spot due to popular content and availability of unpopular video content in a given data center [5]. In one of the paper Adhikari et al. analyze that YouTube is aggressively deploying cache server of widely varying sizes of many different location around the world with several of them located inside other ISPs to reduce cost and improve end user performance. YouTube tries to use local “per-cache” load sharing before resorting to redirection a user to central cache location [10]

2.2 Measurement Of QoE

In measurement of QoE we have divided it into subsection of parameter estimation and impact of influence factor on QoE.

2.2.1 QoE parameter Estimation

QoE is measured subjectively but researcher are trying to measure QoE with objective parameter. Subjective assessment is done by MOS whereas in objective parameter startup

delay, no of rebuffering events, delay of rebuffering events etc are included. In one of the client based approach Barbara Staehle et al. developed a tool YoMo to monitor QoE of YouTube videos. This tool monitors the usage of application their quality requirement and the experienced application comfort at client. They are accurately estimating the player stalling event time [11].

In another approach which is passive monitoring approach in which data is collected by some packet sniffer like wireshark by Raimund Schatz et al. They present 3 methods for in network measurement of QoE impairment that dominate user perception which is rebuffering during playback. They have accurately reconstructed the stalling events by network level measurement [12].

2.2.2 Impact of Influence factor on QoE

When there is a discussion of predicting QoE of YouTube then it is essential to determine key influence factor which have strongest influence on user experience. In 2011, Alessandro Finamore et al. investigated user behaviour and correlated with the system performance. Their results shows that user access pattern are similar across a wide range of user location, access technologies and user devices. They shows that YouTube system is highly optimized for PC access [13]. In one of the paper Louis Plissonneau et al. analyze the impact of YouTube delivery policy on user experience. They crawled the videos to measure QoE. Their analysis shows that geographical proximity does not matter inside Europe or the US, but link cost and ISp dependent policies do, RTT have no impact on QoE and access capacity do not impact QoE [14].

Chapter 3

Methodology

For QoE parameter estimation at first we were using network based approach. In network based approach of estimation passive monitoring is performed with the help of packet sniffer tool called Wireshark. But due to security enhancement of YouTube we could not able to proceed further with network based approach. Then we applied client based approach where a chrome extension is developed which utilizes YouTube API and is installed on client computer for data collection. In first section we introduce data collection tool and in second section we are going to describe about data sets.

3.1 Phase I

In phase I the methodology was passive monitoring approach of YouTube videos where our traces are collected on the tool called wireshark. Wireshark is open source packet sniffer with advanced traffic classification capabilities. Wireshark identifies the application that generate TCP/UDP flows using a combination of Deep Packet inspection and statistical classifier. In the traces we were collecting the QoE parameter like startup delay, seek delay, quality switch etc. But we had to change this methodology because YouTube completely shifted to HTTPS due to which the data which is visible on the traces which has to be analyzed for QoE parameter estimation is encrypted. Due to

encryption of data of traces it is impossible for us to carry on the work with passive monitoring approach.

3.1.1 Experimental setup for phase I

Phase I was based on network based approach , so the analysis is done the traces collected from the wireshark. Wireshark is installed into any intermediate node between client and server or any edge server like proxy server. Fro trace collection process we chose some specific video and created a playlist. These videos are played in script which extract QoE parameter with the help of YouTube API. Analysis of the traces is done and comparison based approach is adopted to verify the result of estimating QoE parameter. The steps of collection of traces are as follows:

- Start wireshark for collecting traces of particular network and apply filter to extract relevant traces.
- Start playback for a predefined playlist of videos.
- Analyze the traces and comparing the parameter with the parameter obtained by script.

3.2 Phase II

Due to failure of network based approach client based approach has been employed to estimate quality of experience parameter. YouTube provide YouTube API for its developer for enhancing YouTube App facility and statistics information for its user. With the help of YouTube API we have developed a chrome extension which will be installed on user's computer and provide QoE parameter in a downloaded file. Chrome extension is a javascript code which automatically start working when YouTube website is opened. As the user starts browsing the website and start playing videos, script starts calling its method so that parameter can be collected at the end of session, user has to click an icon to download the file which contain all the relevant content related to QoE measurement.

3.2.1 DataSets

We collected data sets at university campus over two different network e.g. campus LAN and campus WIFI. Using the chrome extension which we have developed to collect QoE parameter. By the extension we are collecting parameter like startup delay, number of rebuffering events, delay of each rebuffering event and session viewing time etc. Along with QoE parameter we have also collected other metrics such as total video duration and VideoID of currently playing video. After each session of browsing of video file is generated which can be downloaded just by clicking an icon.

3.2.2 Experimental setup for Data collection

We needed to determine impact of influencing factor to determine how much they impact quality of experience parameter. For this purpose we have used different data collection strategies so that data can be gathered accurately , so the data collection has been divided in three different section.

Impact of video duration on startup delay

In this experiment we are trying to determine tolerance level of startup delay of the user in fast campus network.

- Some videos are selected of different duration specifically less than 5 min and greater than 1 hr.
- Bandwidth is throttled with the help of either dummy net or YouTube network throttling feature. For startup delay bandwidth is reduced upto 100 kbps.
- User are asked to watch videos and the data are collected with the help of chrome extension.

Impact of video duration on number of rebuffering events

In this experiment we are trying to estimate the tolerance level of the user for number of rebuffering events.

- This step is same as previous one
- Bandwidth throttling is required to generate rebuffering events. The bandwidth is throttled upto 250 kbps for stall generation.
- When the users navigate after experiencing rebuffering events data is logged on chrome extension.

Impact of network on startup delay

In this experiment we are trying to determine what is the impact of network on startup delay of videos.

- Videos of short length(less than 5 min) are selected. Users are asked to watch videos on LAN network as well as WiFi network of college campus.
- Bandwidth is throttled so that tolerance can be determined. In both the network the bandwidth is throttled to 100 kbps.
- Tolerance level of startup delay of WiFi and LAN are recorded by chrome extension.

Chapter 4

Analysis

4.1 Phase I

Phase I was passive monitoring approach for parameter estimation in which the analysis of the traces collected by wireshark is performed. The traces contain the complete URL information , the messages and the packets exchanged between client and server. The script written for accessing YouTube API is utilized for the experiment. Videos are played in embedded player and at the same time traces are collected. The experiment is conducted for various videos whose length varies from one minute to ten minute. The result of phase I are as follows:

1. Startup delay is one of the QoE metrics which we have successfully estimated. As startup delay can vary according to the available bandwidth and available bandwidth varies with traffic which changes at different time instants of a day and at different locations. Therefore to get variable startup delay, it is evaluated at different time instants of a day and at different locations. It has been seen that scripts which we have implemented has given accurate values which is difficult to obtain when values are in the range of few hundred millisecond. It has been seen that the values obtained from the script are also specified in the traces as a part

of URL. In the figure 4.1 highlighted part is showing the startup delay of 1.407 second embedded in the URL.

2. To determine the seek interval from traces the starting point and the duration of the seek is specified in the script. Script with the help of YouTube API performs seek in the video. This experiment is performed for different starting points with different duration of the seek. From the observations it is found that one of the GET requests shows the information of seek interval. In the figure 4.2 the highlighted value shows seek from 26.614 second to 180 second embedded in the GET request.
3. Clients request for a particular quality of video by specifying itag value. So by observing itag values in url we can find out the quality requested by the client from the server. The variation in itag value gives us the frequency of quality change. In most of the cases it has been observed that a client requests two itag values at a time. With the help of information specified in mime it has been confirmed that one itag value is for audio and another is for video. Thus it can be concluded that clients also change audio quality similar to that of video quality. This is because TCP uses parallel connections for transferring the audio and video content separately. From the experiments it has been observed that every video quality and audio quality has a specific itag value. Most often audio is delivered with itag value 140.

The list of video quality and corresponding itag values are as follows:

- (a) 240p - 133
- (b) 360p - 134
- (c) 480p - 135
- (d) 720p - 136
- (e) 1080p - 137



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initcwndbps=446250&ip=14.139.196.9&ipbits=0&itag=140&keepalive=yes&key=yt5&ln
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FIGURE 4.3: Variation in Quality of Video

- **Tolerance of startup delay-** The time interval in which user switches to another video , refresh the video or quit the video before playing of the video due to high bandwidth fluctuation is known as tolerance of startup delay.
- **Tolerance of number of stall-** It is defined as number of stalls after which user will quit the video or switches to another video during playback because of underrun of buffer.

4.2.1 Impact of video duration on startup delay

Fig 4.4 and 4.5 shows the variation of startup delay when the video duration are short and long respectively. Note that video duration are total duration of video not fraction of video watched during session by the user. Consider the short length video scenario, the measurement from the dataset shows the tolerance level user in fast campus network. From the graph it is clear that video duration has significant impact on startup delay tolerance of the user. For example the CDF function clearly shows that in long duration videos 60% of users are ready to wait for 7 to 9 second whereas for short video 60% of users are waiting only from 4 to 6 second. We see the moderate difference of 3 second of tolerance when video duration is changed from short to long. As initial buffering is

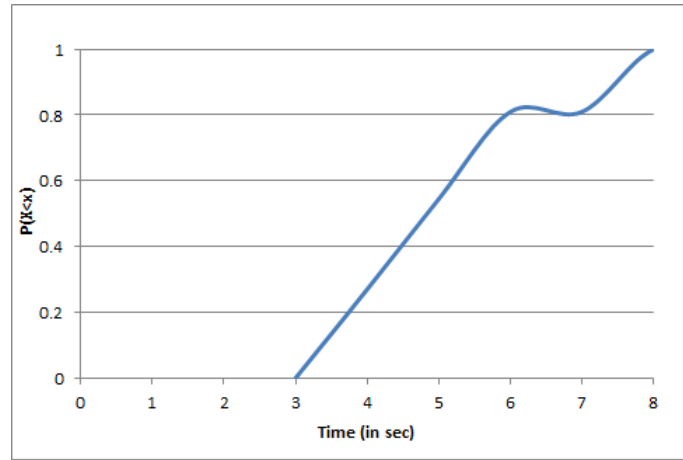


FIGURE 4.4: CDF of startup delay of short duration videos

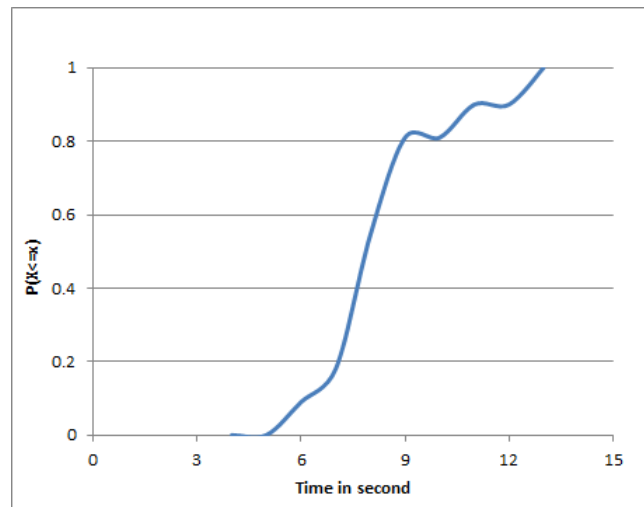


FIGURE 4.5: CDF of startup delay of long duration videos

considered it is upper bound of tolerance a user would ready to tolerate in startup delay in fast campus network.

4.2.2 Impact of video duration on number of rebuffering events

Fig 4.6 and 4.7 is a CDF function of number of buffering events in long duration and short duration videos. Here the rebuffering events are lesser than 5 seconds, for the longer interval of rebuffering events the data can vary. Consider the CDF function for short duration video, the measurement shows the tolerance of number of rebuffering events for users. From the graph variation can be clearly seen for both video duration type such that

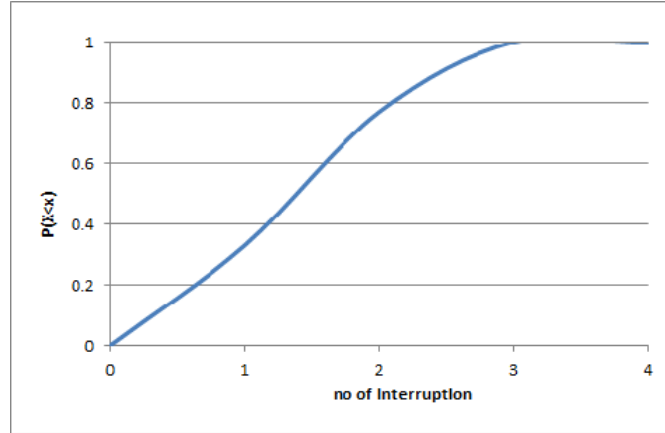


FIGURE 4.6: CDF of startup delay of short duration videos

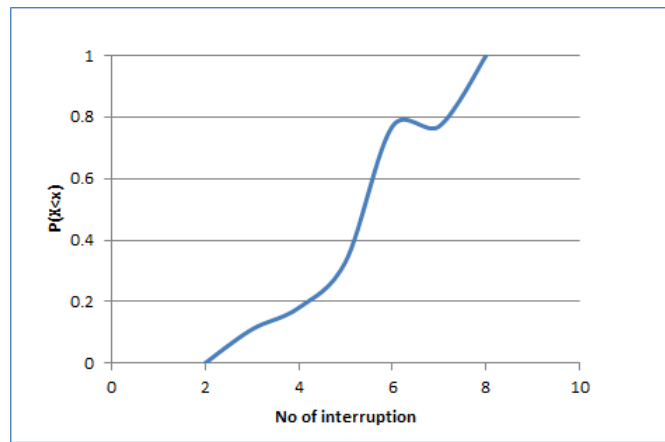


FIGURE 4.7: CDF of startup delay of long duration videos

77% of user prefer 2 or less than 2 rebuffering events for short duration video whereas 59% of the user prefer 4 to 6 rebuffering events for long duration videos. The data is taken for rebuffering events that is shorter than 5 seconds, if the rebuffering events is large enough then user may quit quite early for large duration videos.

4.2.3 Impact of network on startup delay

Fig 4.8 and 4.9 shows the variation of tolerance of startup delay when the network type is LAN and WiFi respectively. Here the video are taken has shorter length and the measurement is performed for type of network. From the graph we can observe that for the LAN network users are less tolerant than WiFi network. The data shows that 77% users tolerate for 5 seconds or less when they use LAN network whereas the time goes

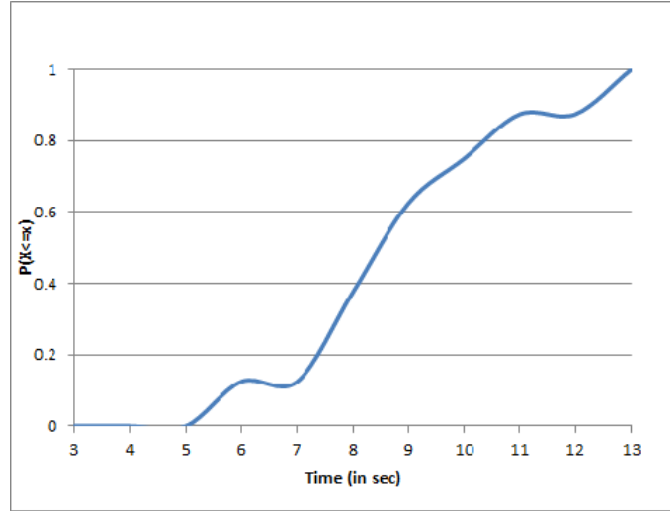


FIGURE 4.8: CDF of startup delay of WIFI network

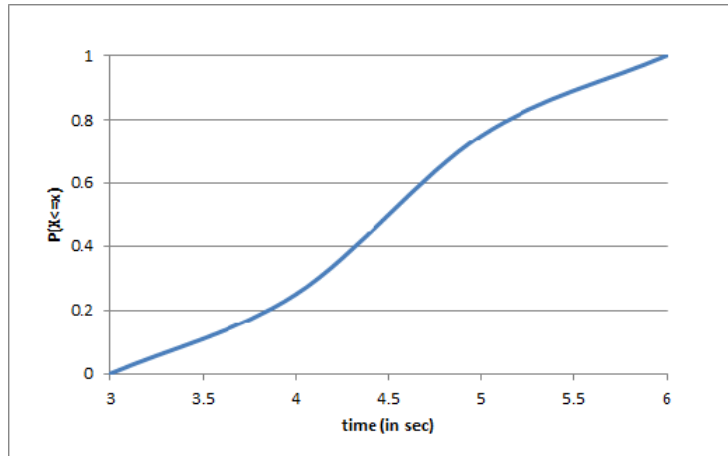


FIGURE 4.9: CDF of startup delay of LAN network

up to 7 to 11 seconds for 75% of the users, when they use WiFi network. The possible reason for such a high tolerance for WiFi is that user knows that WiFi is much slower than LAN network or they have past history of slow WiFi experience due to which they are ready for experiencing much higher startup delay.

Chapter 5

Conclusion

With the help of chrome extension we have estimated QoE parameter and with moderately large data sets we have shown impact of video duration and network on startup delay and rebuffering events. By the result it is clear that video duration impact QoE parameters like startup delay and no of rebuffering events. Type of network is also one of the influencing factor that causes changes in QoE parameter. Our result shows significant variation of QoE parameter with influencing factor.

Chapter 6

Future Work

As future work, we aim at extending our conclusion by adding more network like 2G/3G. We would like to include influencing factor like type of device, type of content etc. Our chrome extension works only with YouTube we will like to extend it for more streaming content distributor like dailymotion, metacafe etc. One of the interesting direction of research is to compare the QoE parameter of the same video for different streaming content distributor website.

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