

Delivering solutions in ABR Video Streaming: approaches and open Researches

Pesaresi Seminar - Università di Pisa

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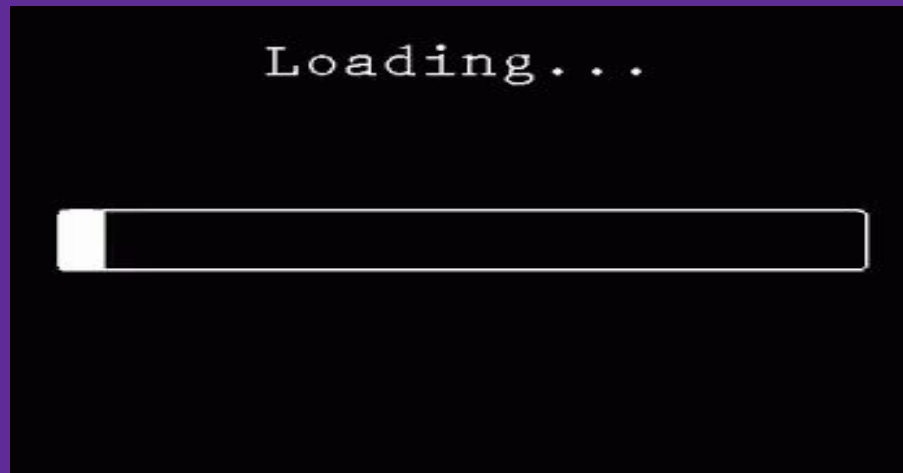
INTRODUCTION

Video Streaming Context

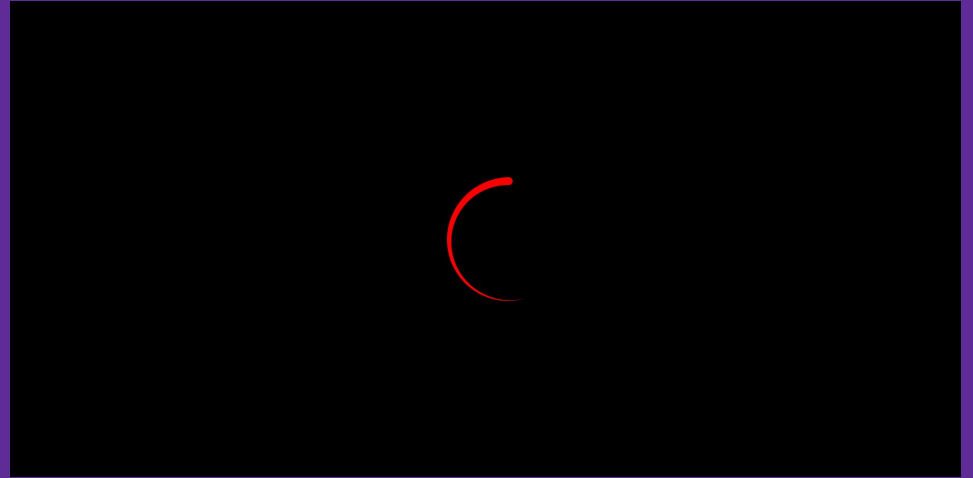
- Streaming On-demand
- Live Streaming
- Heterogeneous Network conditions
 - Restricted bandwidth
 - Network fluctuations
 - High number of End-clients



Video Streaming Common situations 1

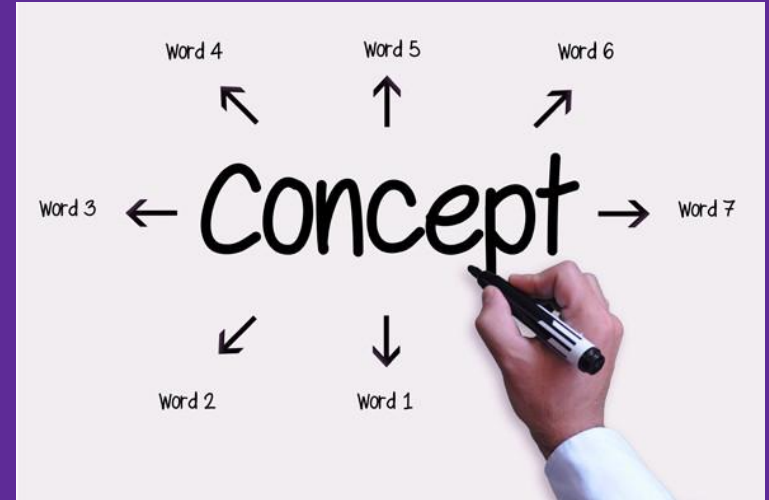


Video Streaming Common situations 2



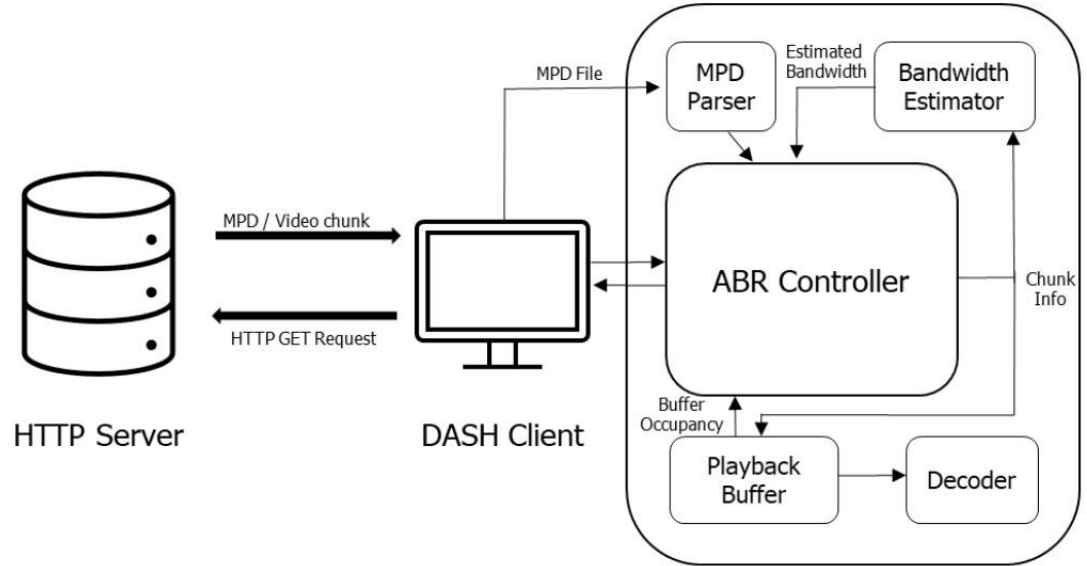
FUNDAMENTAL CONCEPTS

let's understand some concepts...



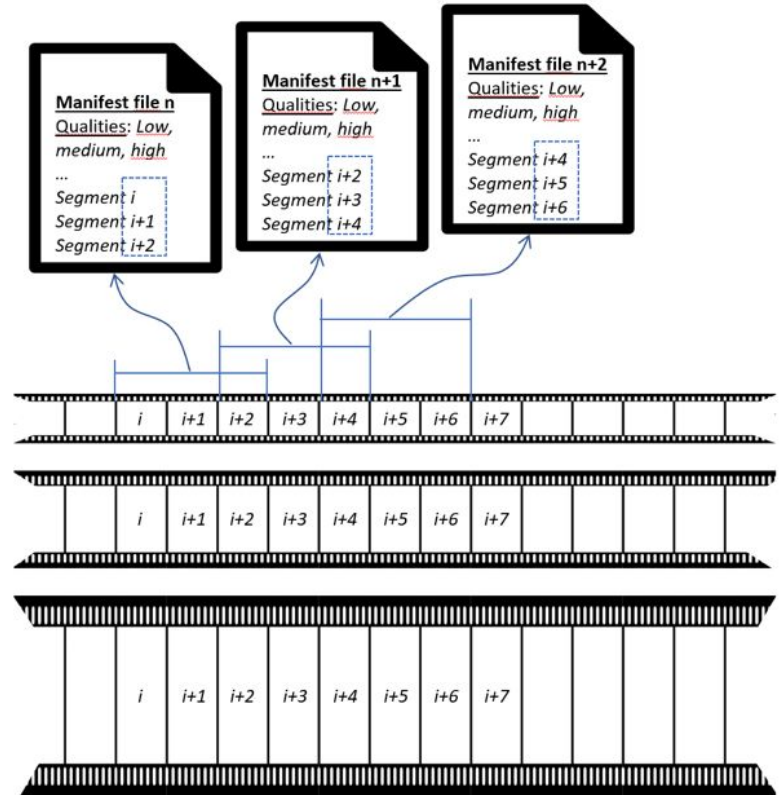
Adaptive Video Streaming - explaining

- Work in HTTP transmission
- Don't need manage transfer policies through TCP layer (TCP-based HTTP protocol)
- Provides feedback to the server
- Common Technologies:
 - HLS (Apple HTTP Live Streaming)
 - HDS (Adobe HTTP Dynamic Streaming)
 - DASH (Mpeg Standard)



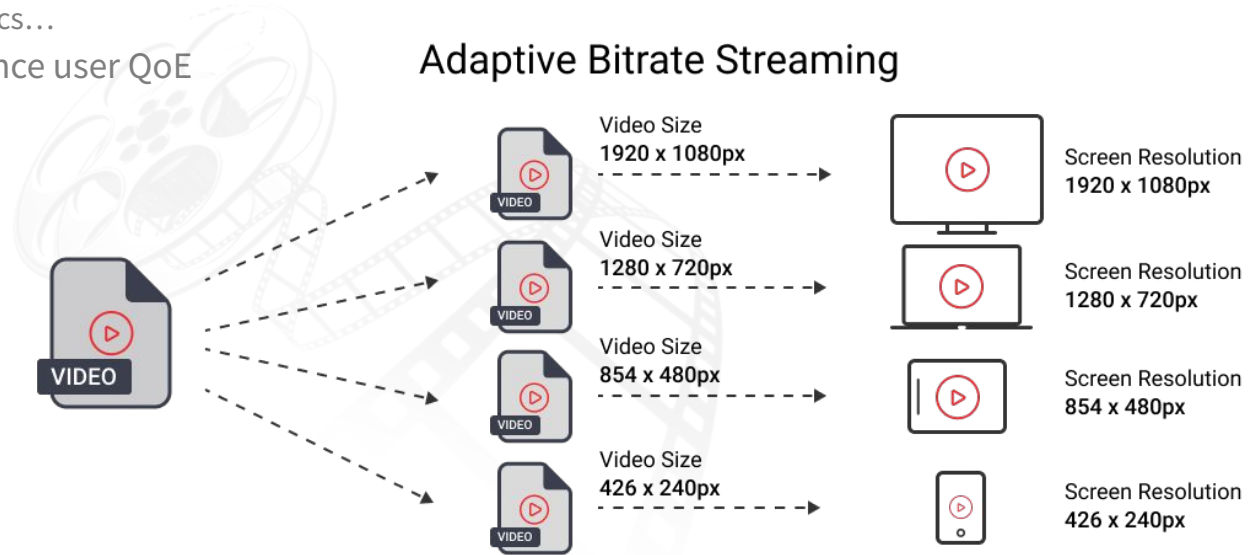
Adaptive Video Streaming - explaining

- Video is pre-stored on a server as multiple segments
 - Each segment containing a portion of the video
 - A video segment is encoded to have various qualities for different conditions
- Clients request and downloads the **Media Presentation File (MPD)**
 - bitRate, size, playback length, request address...

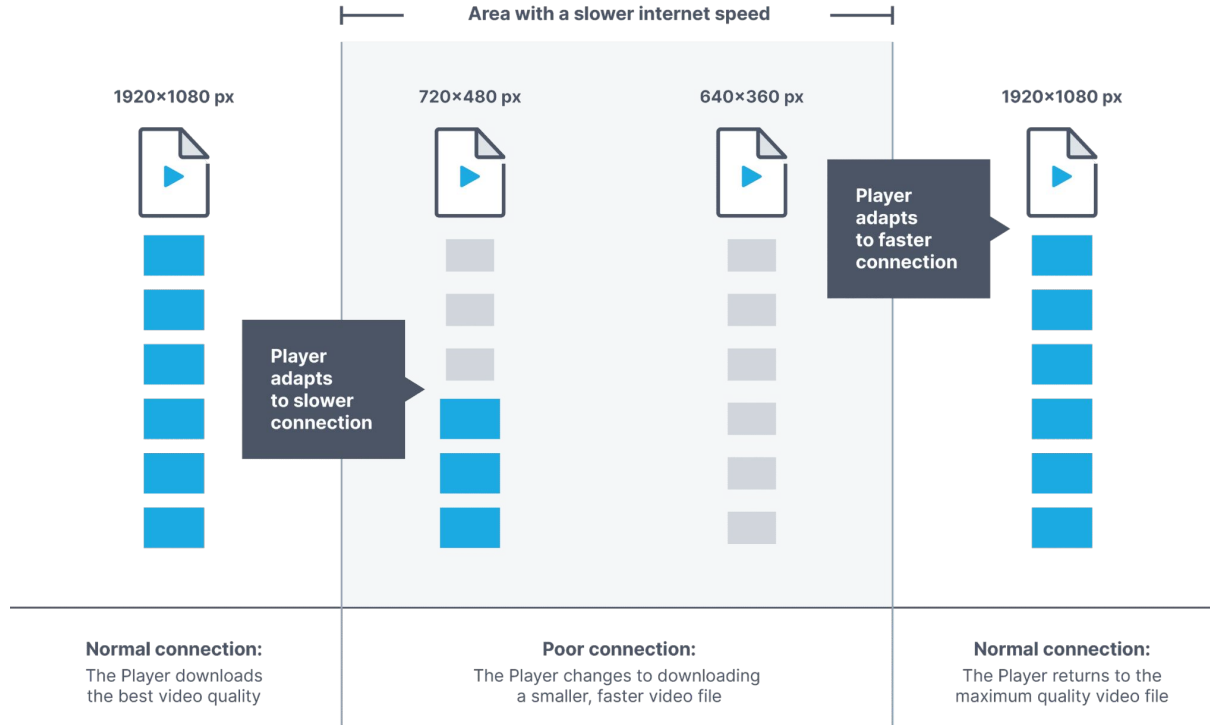


Adaptive Video Streaming - explaining

- Download different segments (chunks) analyzing context information
 - Network status, user buffer, video characteristics...
- Focused to enhance user QoE



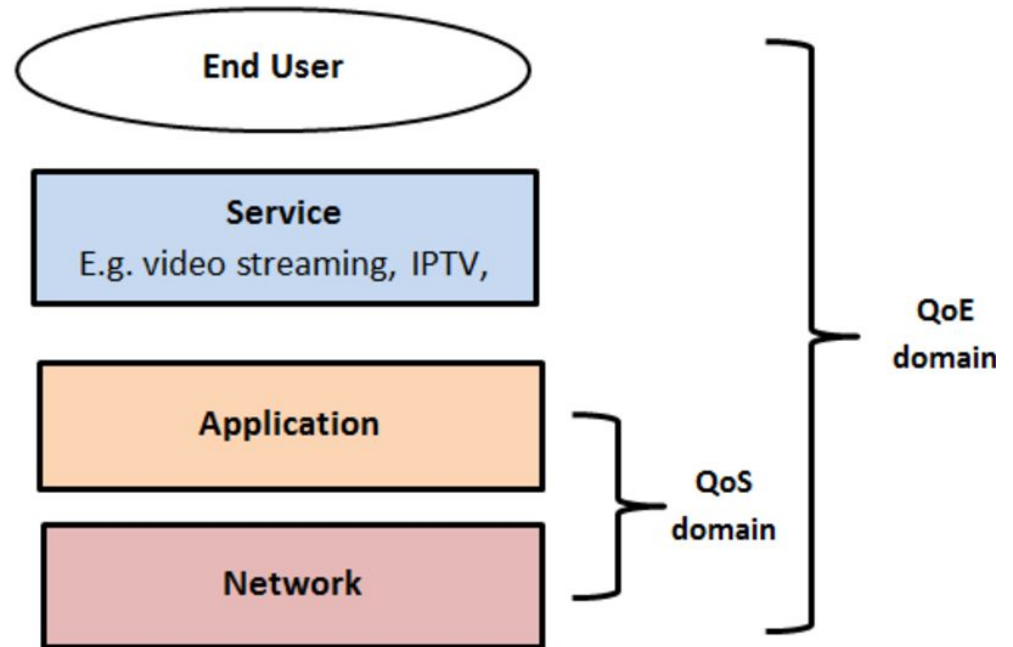
Adaptive Video Streaming - explaining



Bitrate switching process...

QoE? Quality of experience...

- Refers at the term "Quality of Experience"
 - Focused in user conditions criteria...
- Main metrics mechanisms
 - Mean score opinion (MOS)
 - 0 ... 5
 - International Telecommunication Union (ITU-T)
 - Initial Playback delay, Rebuffering ratio, Video quality, Video freeze ratio...
- Multidisciplinary approach
 - Most quality assessment methods consider system factors



User factors

Physiological:

- Age, gender, ethnic origin
- Mood
- Mental states

Behavioral:

- Preferences
- Expectations
- Purpose of use
- Emotions, motivation
- Visual/audio acuity
- Tiredness, distraction
- Distance from device
- Clothes, hat, jewelry
- Glasses/contact lenses
- Ergonomics

Lower control

Context factors

Environmental:

- Indoor/outdoor operation
- Temperature, humidity
- Illumination, light, reflection
- Ambient noise

Temporal:

- Time, cycle of use

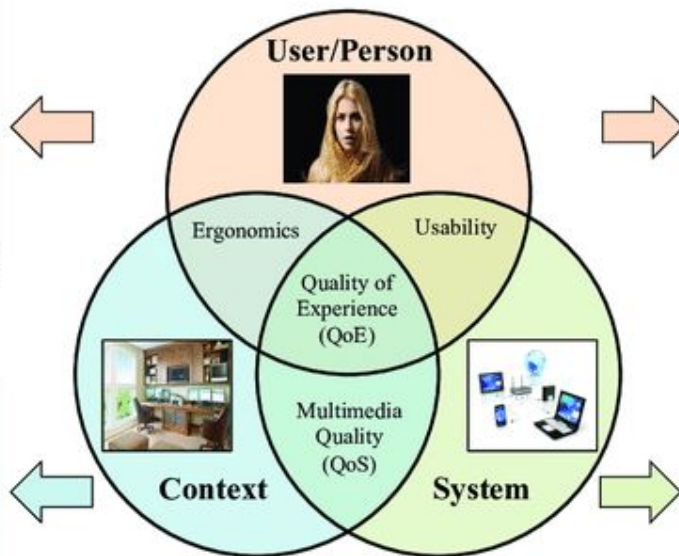
Social:

- Interpersonal relationship

Economics

- Cost, brands

Medium control



System factors

At user side

Device:

- User familiarity
- Ease of use and maintenance
- Device performance
- Physical robustness
- Resolution, noise, echo
- Input/output naturalness
- Multimedia content (e.g., news/movies)
- Audio/video bitrate

At system side

Data:

- Exchange and storage format
- Processing algorithms
- Bandwidth
- Data compression
- Networks and their performances
- Transmission parameters (e.g., jitter, delay, buffering, loss, throughput)

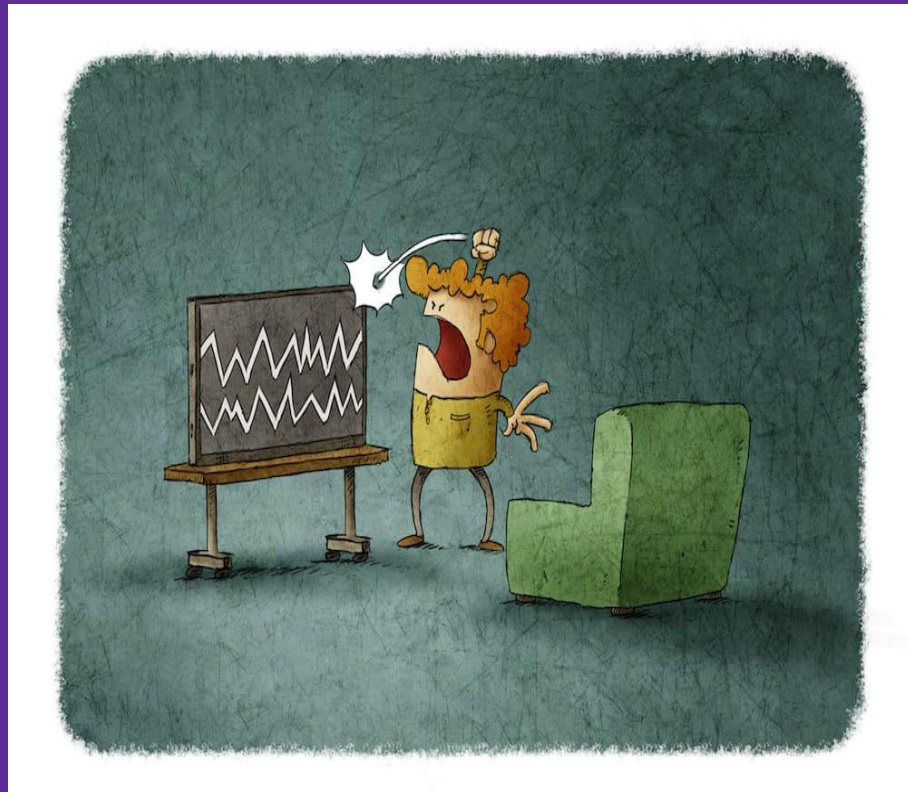
Higher control

Loading...



If QoE is bad

we have problems...



Challenges for ABR Streaming

- Manage Network Conditions, Buffer Size and device limitations.
- Generally do not consider client device type and video characteristics
 - Wasting network Bandwidth
- Cannot ensure that the QoE of all video streaming clients remain at a high level
- Real-time adaptation
 - Make instantaneous decisions based on rapidly changing network conditions



bitrate bitrate-levels buffer delay end-to-end-
delay fixed-buffer-threshold **latency** less-
rebuffering live-streaming playback playback-interruption playback-
levels **qoe** qoe-based qoe-degradation **qos** quality-
of-experience quality-of-service
rebuffering stalls streaming-
on-demand **throughput**

ABR Streaming-Based model

Let's delivering our video streaming
avoiding problems...



Dynamic BitRate Adaptation models

Rate-based

Focus: estimate the available bandwidth and adjust the bitRate accordingly.

metrics: Often use throughput and round-trip time measurements.

Weakness: high network variability or sudden changes in bandwidth

Buffer-based

Focus: Focusing in monitoring the buffer-occupancy and manage the buffer level. Good for consistent conditions.

Metrics: Often use buffer-occupancy measurement

Weakness: Highly variable network environments

Content-aware

Focus: Consider the characteristics of the video itself.

Metrics: Often uses scene complexity, motion and visual details.

Weakness: predict content characteristics in real-time or adapting to diverse viewer preferences

Dynamic BitRate Adaptation models

Machine Learning-based

Focus: Can analyse historical data on network conditions, viewer behavior, and content characteristics to predict future conditions.

Continuously learn from streaming sessions to make proactive decisions.

Metrics: variable according the model adopted

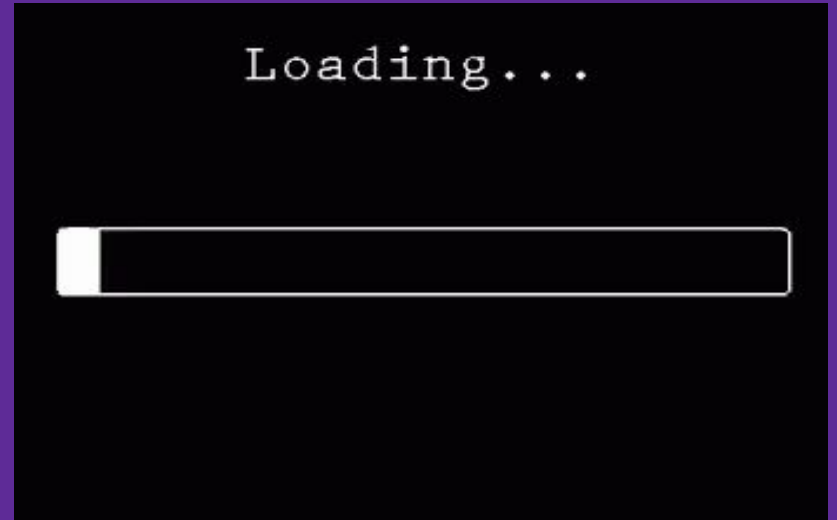
Weakness: Model development, model training and computational intensive.

Dash-Based Streaming metrics

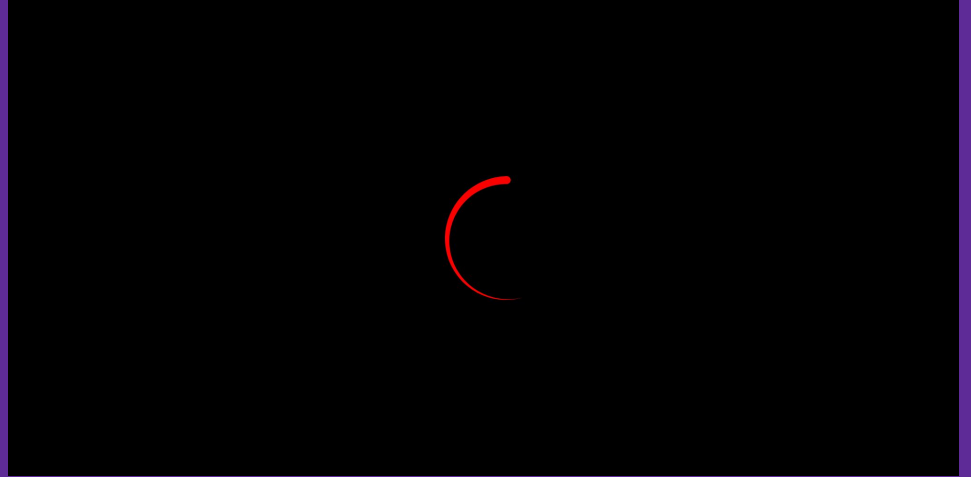
- There are 4 main metrics that Govern QoE in a DASH session
 - **Video Buffer**
 - Available video buffer in a client
 - **Initial Playout Delay**
 - time between client play and video starts playing
 - **Rebuffering**
 - Number and duration of rebuffering (freezing)
 - **Video Quality Switching** statistics
 - Bitrate segments
 - Number of quality switching events



**Initial playout
delay or
startup-delay...**



rebuffering...

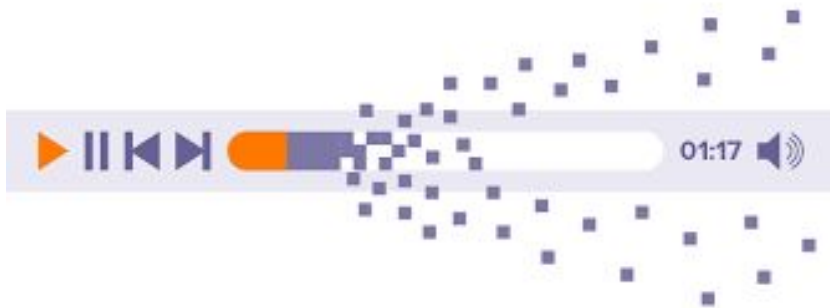


Latest Trends in Dynamic ABR Streaming



- Machine Learning Integration
 - Dynamic bitrate adaptation
- Context-aware Adaptation
 - Holistic understanding viewing context
- Ultra Low-latency Streaming
 - Minimizing delay between user interactions and content playback
- Content-driven Adaptation
 - Understand and adapt to the characteristics of the video itself
- Dynamic Packaging and Multi-codec Support
 - Delivering content in multiple formats and resolutions

Potential Areas/Open researches



- QoE-Based applications
 - Developing QoE metrics
 - QoE Fairness
 - QoE Aware
- Real-Time Context Awareness
 - Providing more granular information by sensors devices
- Edge Computing for Adaptive Streaming
 - Collaborative MEC
 - QoE Aware
 - Caching Strategies
- Personalized BitRate Adaptation Policies
 - By user-based patterns and making ABR decisions
- Interactivity and Immersive Experiences
 - Adapt varying network conditions and interactive 360-degree content videos

STUDY CASES: ML-based

Study Case: ML-Based Methods

- **Netflix**

- Optimizes video encoding parameters in real time based on *content characteristics* and *network conditions*
- Employing **Reinforcement Learning** to *adapt requirements of each video*
- Enhancing visual quality and reducing bandwidth usage
- applies **Edge Caching** combined with a clustering approach for heavy tail contents

- **Amazon Prime**

- *User-centric* approach
- Employs ML to *analyse user behavior, device capabilities* and *network conditions*

- **Youtube**

- Employs machine Learning algorithms for real-time bitrate adaptation
 - Considering factors like video complexity and user preferences
 - **dwell** QoE metric to measure user engagement
- Employs HTTP-DASH protocol

How ML can help ABR-Streaming?

Reinforcement Learning based approaches...

- Learning from interactions with the environment aligns well with the dynamic nature of streaming scenarios.
 - Predict user behavior
 - Analyse network conditions
 - Analyse feedback from devices
- Low-latency decision-making
 - Adapt bitRate delivering
 - Adjust Buffer conditions

HTTP Adaptive Streaming Framework with Online Reinforcement Learning

Abstract: Dynamic adaptive streaming over HTTP (DASH) is an effective method for improving video streaming quality of experience (QoE). However, the majority of existing schemes rely on heuristic algorithms, and the learning-based scheme that has recently emerged also has a problem in that their performance deteriorates in a specific environment. In this study, we propose an adaptive streaming scheme that applies online reinforcement learning. When QoE degradation is confirmed, the proposed scheme adapts to changes in the client's environment by upgrading the ABR model while performing video streaming. In order to adapt the adaptive bitrate (ABR) model to a changing network environment while performing video streaming, the neural network model is trained with a state-of-the-art reinforcement learning algorithm. The proposed scheme's performance was evaluated using simulation-based experiments under various network conditions. The experimental results confirmed that the proposed scheme performed better than the existing schemes.

Keywords: dynamic adaptive streaming over HTTP (DASH); quality of experience (QoE); reinforcement learning; online learning



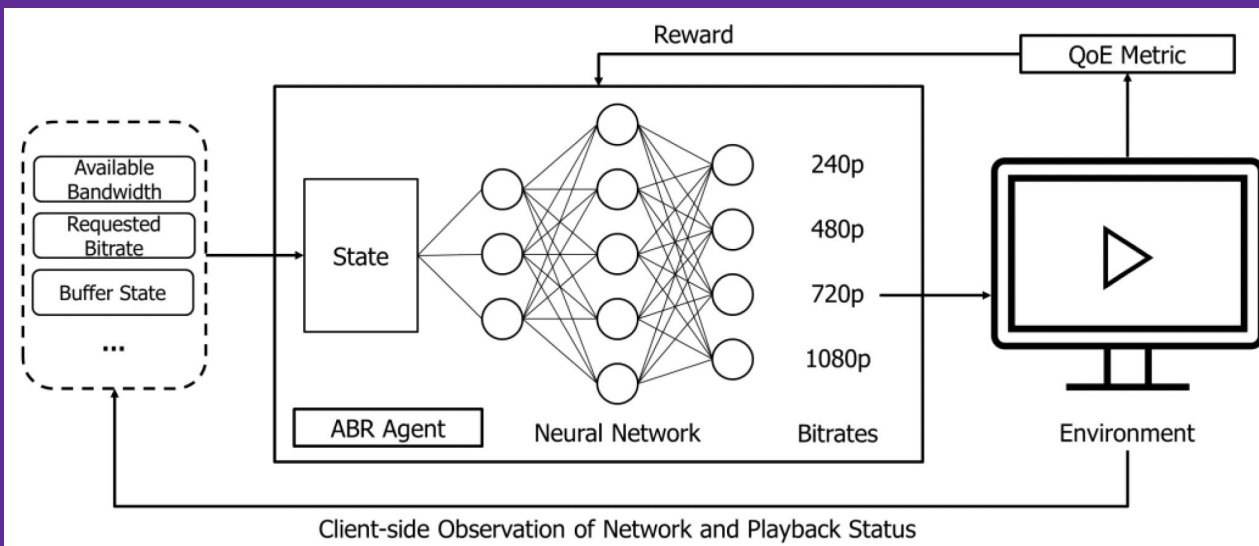
Jeongho Kang, Kwangseok Chung, K. HTTP Adaptive Streaming Framework with Online Reinforcement Learning, *Appl. Sci.* 2022, 12, 7425. <https://doi.org/10.3390/app12127425>

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1. Introduction

With the proliferation of various smart devices and network development, the number of users accessing video streaming services via the Internet has recently increased. According to the Cisco Annual Internet Report, the total number of Internet users worldwide will increase from 51% of the population in 2018 to 66% of the population by 2023 [1]. Video streaming services such as YouTube and Netflix account for the majority of internet traffic. With the growing importance of video streaming services, HTTP adaptive streaming is gaining traction as a technology to provide users with a high quality of experience (QoE) [2]. Dynamic adaptive streaming over HTTP (DASH) was established as a standard for HTTP adaptive streaming technology in 2011 as a solution to provide efficient and smooth video streaming [3]. DASH has high reliability and is not restricted by firewalls and network address translations (NATs) because it uses the existing TCP-based HTTP protocol. In addition, it has high scalability because it improves QoE by adjusting the quality of video segments delivered through the network on the client side. Commercialized services include Microsoft's Smooth Streaming, Apple's HTTP Live Streaming, and Adobe's HTTP Dynamic Streaming [4–6].



Thank you for listening

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