Improving Quality of Experience in Adaptive Video Streaming

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Introduction

Problem Statement

Improve user-centric measures of video streaming quality

Quality of Experience

QoE is a number describing user’s satisfaction with video streaming. However, it is not possible to measure this number directly.

Typical approximations include combinations of system-level, machine-centric measurements, e.g., stalling, average segment quality, startup time, quality fluctuation frequency. Other methods include user surveys – unsuitable for large-scale studies.

Proposed Work

Optimize streaming quality to improve direct indications of user satisfaction. For example, video abandonment.

Optimize with respect to better measurement will better improve video streams.

Also, these direct quality measures allow us to do user-specific optimization.

Background

DASH

(Dynamic Adaptive Streaming over HTTP) allows a streaming client to request video segments of varying bitrates depending on conditions in the network and on the device. This adaptation improves the user experience of video playback by minimizing re-buffering and stall events at the expense of streaming bitrate.

Buffer-based Adaptation

Other Adaptation Approaches

Model predictive control

\[ \text{QoE} = \text{QoE}_{\text{video}} + \text{QoE}_{\text{network}} \]

Typical approximations include

- Video abandonment
- Empirical throughput
- Buffer state

DASH

- Dynamic Adaptive Streaming over HTTP

Other adaptation approaches

- Model predictive control
- Reinforcement learning

Future Work

- Incorporate direct indications of user satisfaction into the MDP reward function
- Train user-specific MDPs to allow bitrate adaptation that adjusts to user preferences

Trained Adaptive Streaming

A prediction-free, reinforcement-learning-based approach

Summary of Our Approach

- Formulate the bitrate adaptation problem as a Markov Decision Process
- Use Q-learning approach
- Approximate Q-function with multi-layer perceptron
- Inputs to the Q-function approximation:
  1. Current quality level
  2. Empirical throughput
  3. Current buffer state
- Linear QoE approximation with terms including overall quality level, quality fluctuation, rebuffer events

Results

Cumulative Fraction

-40 -20 0 20 QoE

Extend and improve reinforcement learning approaches

- Incorporate direct indications of user satisfaction into the MDP reward function
- Train user-specific MDPs to allow bitrate adaptation that adjusts to user preferences

Other Adaptation Approaches

Tabular-based Q-learning

\[ Q(s,a) = \sum_{s'} R(s,a,s') + \gamma \max_a Q(s',a) \]

Dash.js

BB-RL

RBB-RL

Collect user-specific improvements of quality of experience for video streaming

Data Collection

Client

Media Player

Playback statistics, e.g., empirical throughput, buffer state, etc.

Adaptation

Decision

Mini-batches of tuple (old state, new state, action, reward)

Model Training

push new model to the client