SENSEI: Aligning Video Streaming Quality with Dynamic User Sensitivity

Xu Zhang, Yiyang Ou, Siddhartha Sen, Junchen Jiang
Network bandwidth is insufficient for desirable QoE

Goal: Better QoE for more users given limited bandwidth!
Conventional wisdom

Treat video chunks *equally* when the player choose bitrate for chunks

**Key insight:** Users have *different* quality sensitivity to the chunks

Let’s see an example...
Video A
Video B
Which video has better quality?
Different quality tolerance to rebuffering

Each ↓ indicates a 1-second rebuffering
Quality sensitivity varies with video content!
Roadmap

1. Demonstrate high variability of quality sensitivity in real videos

2. Quantify this quality sensitivity reliably

3. Leverage this quality sensitivity to improve adaptive video streaming
Quality sensitivity is highly variable

QoE drop $\Delta$ at time $t = \text{rating under highest quality} - \text{rating with 1-sec rebuffering at time } t$

Opportunity: Large variability enables us to trade off insensitive chunks for sensitive ones
Incorporating quality sensitivity into a QoE model

Traditional QoE model

\[ QoE = \frac{1}{N} \sum_{i=1}^{N} q_i \]

SENSEI

\[ QoE = \frac{1}{N} \sum_{i=1}^{N} w_i(q_i)q_i \]

- \( q_i \) - QoE estimates of chunk \( i \) in traditional models
- \( N \) - Number of chunks
- \( w_i(q_i) \) - the weight of chunk \( i \) with quality \( q_i \)

Reweight the chunks by their quality sensitivity in a QoE model
How to capture content-dependent quality sensitivity

Strawman: Directly use video saliency models
- Pixel-motion-based models, *e.g.*, AMVM
- Interestingness score models, *e.g.*, Video2Gif, DSN

Saliency models regard it as sensitive

Our user study regards it as sensitive

The purposes of the saliency models do not align with quality sensitivity
Idea: Directly ask for quality sensitivity by crowdsourcing

**Pros**
- **Directly** link video quality to QoE
- Worth the cost for **popular** on-demand videos

**Cons**
- High cost to evaluate every chunk and every type of low-quality event.
- Response reliability affecting the QoE model accuracy
- Not support live-video streaming
Reducing the crowdsourcing cost

**Idea:** Coarse quality sensitivity
- Group chunks that might have similar quality sensitivity
- Zoom in the representative chunks in each group

**Two-step scheduling**

1. **Step 1:** Identify chunks that share weights
2. **Step 2:** Zoom in the representative chunks 1,2 to get the weight $w_i(q_i)$
Improving response reliability

**Challenge**: Crowdsourcing workers might provide random responses

Quality control scheme
- Engagement test
- Control questions
- Randomized video order
- Use Master Turkers

More reliable responses makes higher accuracy of the QoE model
Protect quality sensitive video chunks

New action: Lower the quality of insensitivity chunks to get high quality for sensitive chunks

Tradition rebuffering

Sensei’s rebuffering
Evaluation setup

Dataset
16 videos from LIVE-MOBILE, LIVE-NFLX-II, WaterlooSQOE-III and YouTube-UGC
Categories: Animation, Gaming, News, Sports
network throughput traces from FCC and 3G/HSDPA (0.2Mbps – 6Mbps)

Baseline ABR algorithms: Fugu, Pensive, BBA
Sensei achieves higher QoE

Sensei has **15.1%** higher QoE under the same bandwidth
Sensei can save bandwidth

Sensei has **26.8%** less bandwidth usage but the same QoE as other ABR algorithms.
Sensei’s cost

Sensei’s cost is ~$31.4 per minute video
Saving ~30x compared with the crowdsourcing w/o cost pruning
Accuracy of Sensei’s QoE model

QoE impact by number of crowd workers

Parameter selection for user study

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Xu Zhang  
University of Chicago

Yiyang Ou  
University of Chicago

Siddhartha Sen  
Microsoft Research

Junchen Jiang  
University of Chicago

Abstract

This paper aims to improve video streaming by leveraging a simple observation—users are more sensitive to low quality in certain parts of a video than in others. For instance, rebuffering during key moments of a sports video (e.g., before a goal is scored) is more annoying than rebuffering during normal gameplay. Such content-dependent dynamic quality sensitivity, however, is rarely captured by current approaches, which predict QoE (quality-of-experience) using one-size-fits-all heuristics that are too simplistic to understand the nuances of diverse video content.

The problem is that none of these approaches know the true

recent adaptive bitrate (ABR) algorithms (e.g., [45, 56, 83]) achieve near-optimal balance between bitrate and rebuffering events, and recent video codecs (e.g., [54, 72]) improve encoding efficiency but require an order of magnitude more computing power than their predecessors. The confluence of these trends means that the Internet may soon be overwhelmed by online video traffic, and new ways are needed to attain fundamentally better tradeoffs between bandwidth usage and user-perceived QoE (quality of experience).

We argue that a key limiting factor is the conventional wisdom that users care about quality in the same way throughout a video, so video quality should be optimized using the same standard everywhere in a video. This means that know
Observation: For viewers, quality sensitivity varies as video content changes

Key idea: Embrace variability of quality sensitivity using sensitivity weights obtained via per-video crowdsourcing

SENSEI improves video QoE by 15.1% or save bandwidth by 26.8% on average with a cost of $31.4 per minute video