SENSEI: Aligning Video Streaming Quality with Dynamic User Sensitivity

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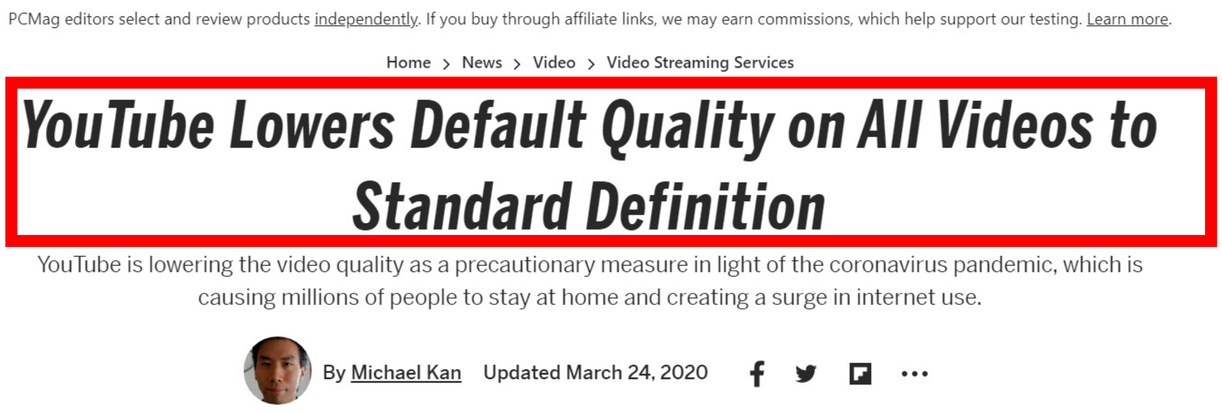
Network bandwidth is insufficient for desirable QoE



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YouTube Lowers Default Quality on All Videos to Standard Definition

YouTube is lowering the video quality as a precautionary measure in light of the coronavirus pandemic, which is causing millions of people to stay at home and creating a surge in internet use.

By Michael Kan Updated March 24, 2020

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Reducing Netflix traffic where it's needed while maintaining the member experience

Ken Florance
VP Content Delivery

Goal: Better QoE for more users given limited bandwidth!

Conventional wisdom

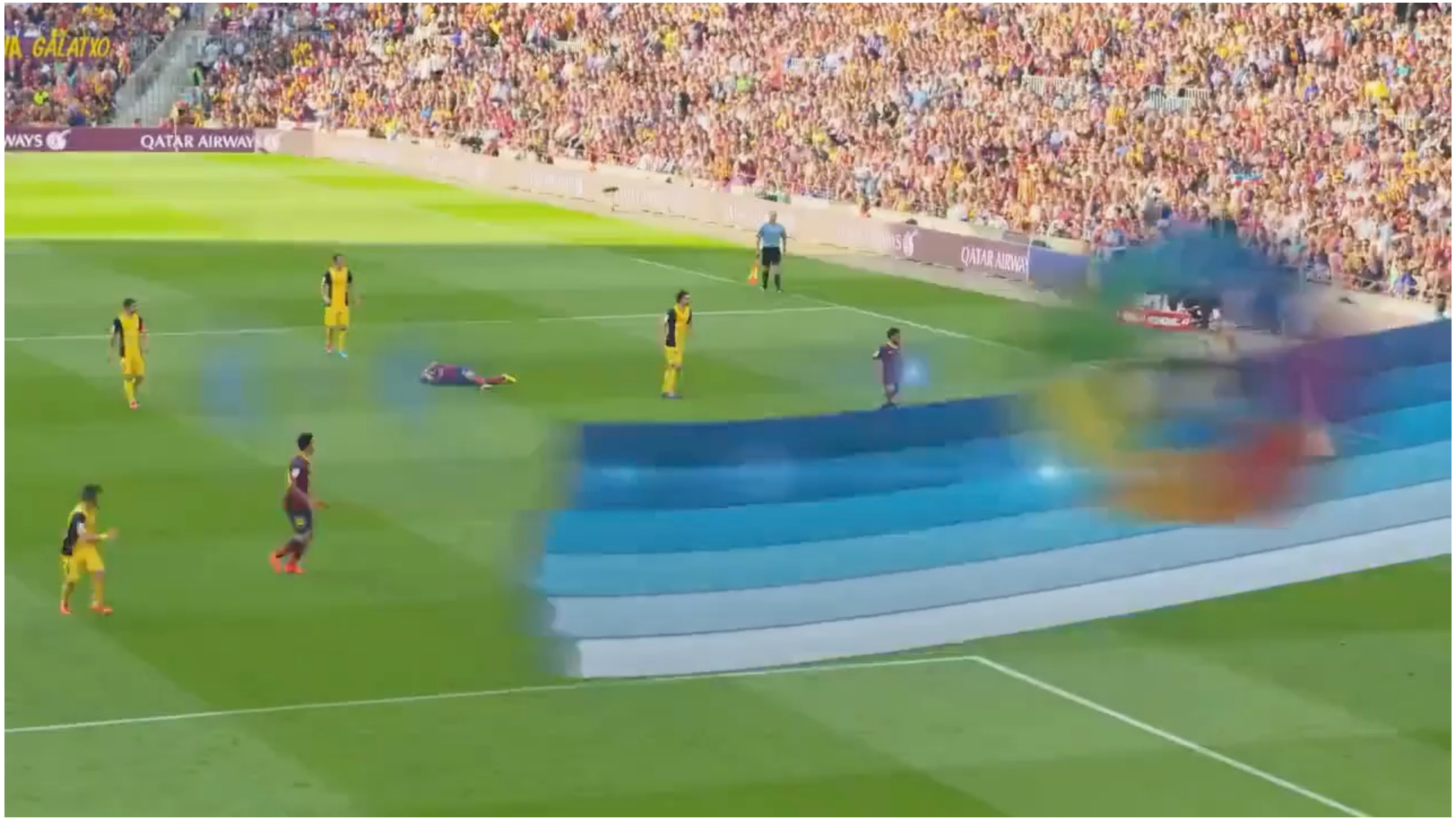
Treat video chunks **equally** when the player choose bitrate for chunks

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

Let’s see an example…

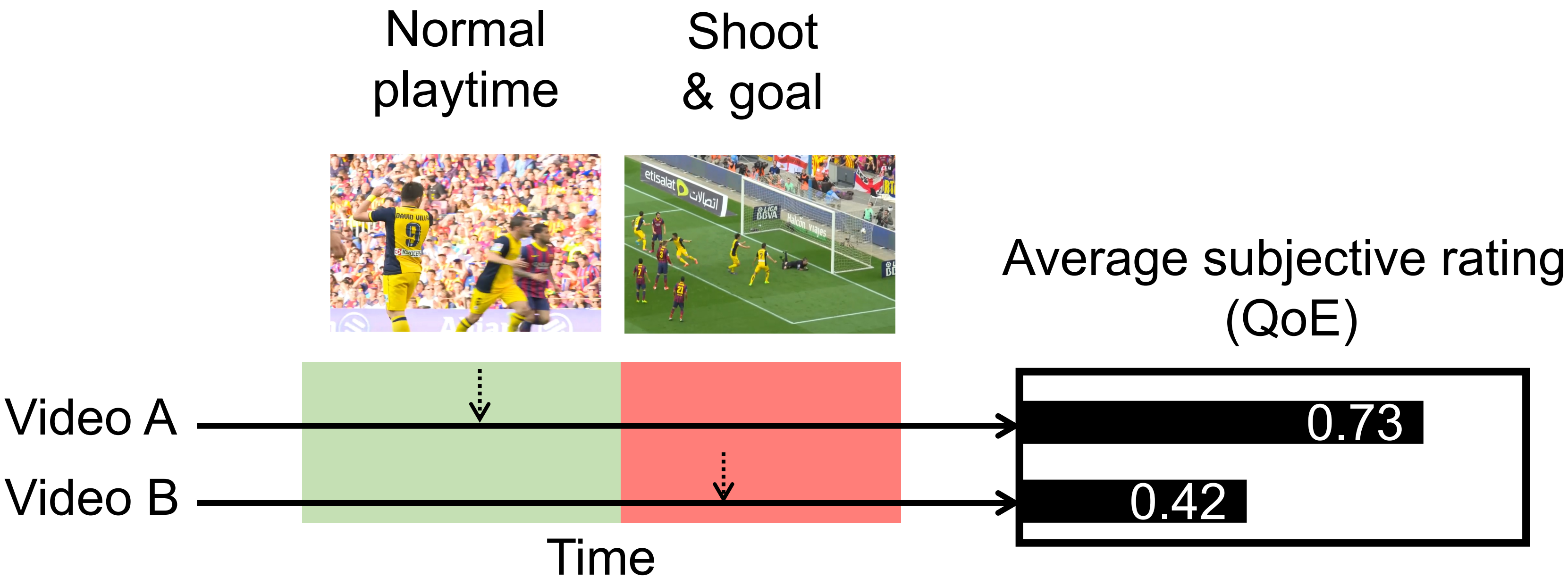
Video A

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

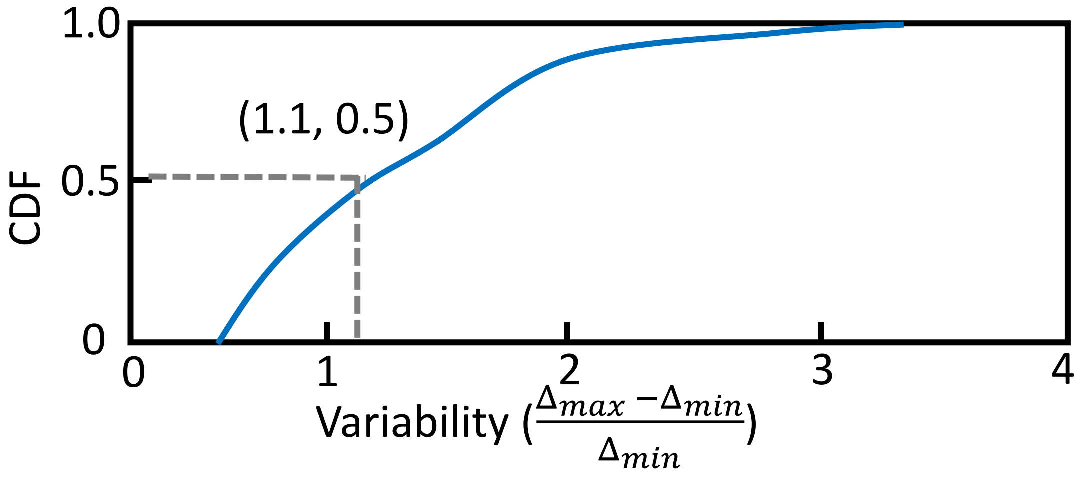
1. Demonstrate high variability of quality sensitivity in real videos

2. Quantify this quality sensitivity reliably

3. Leverage this quality sensitivity to improve adaptive video streaming

Quality sensitivity is highly variable

QoE drop Δ at time t = rating under highest quality – rating with 1-sec rebuffering at time t



QoE drop could vary >110% for 50% videos!

Opportunity: Large variability enables us to trade off insensitive chunks for sensitive ones

Incorporating quality sensitivity into a QoE model

Traditional QoE model

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

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$$QoE = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{w_i(q_i)} q_i$$

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

Normal playtime

Insensitive part

Shoot & goal

Sensitive part

The purposes of the saliency models do not align with quality sensitivity

Idea: Directly ask for quality sensitivity by crowdsourcing

<u>Pros</u>

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

<u>Cons</u>

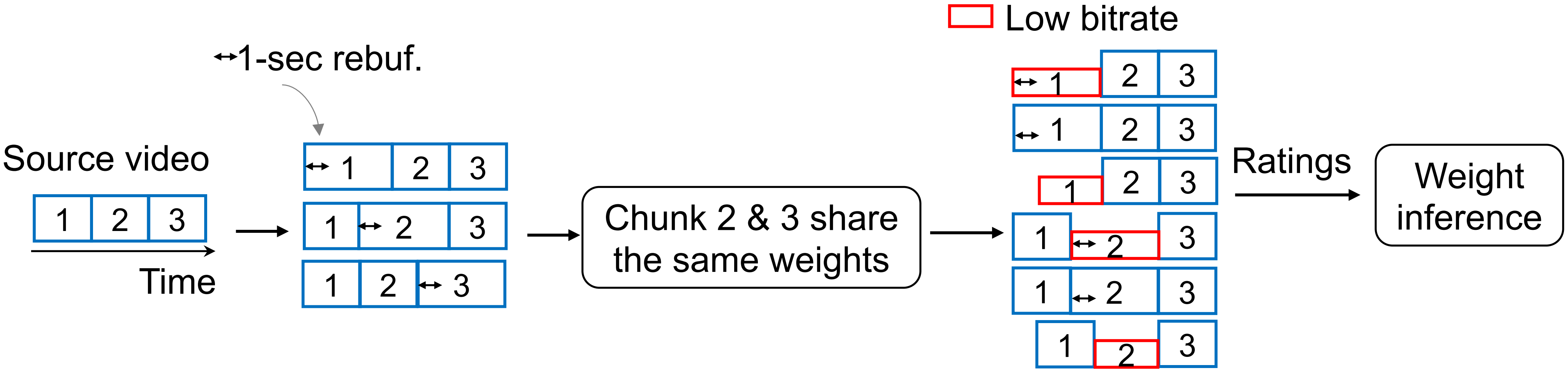
- High cost to evaluate every chunk and every type of low-quality event.
- Response reliability affecting the QoE model accuracy
- Not support live-video streaming

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



Step 1: Identify chunks that share weights

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

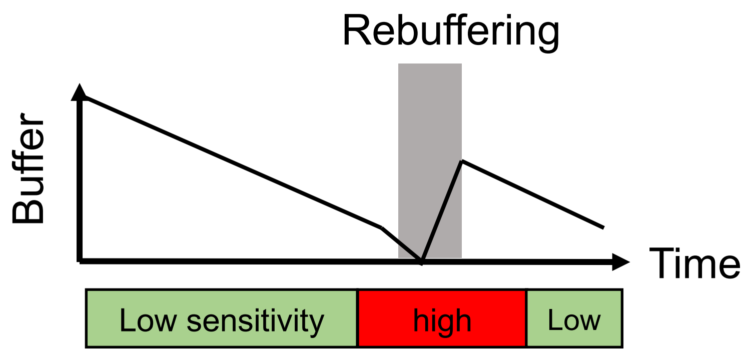
Quality control scheme

- Engagement test
- Control questions
- Randomized video order
- Use Master Turkers

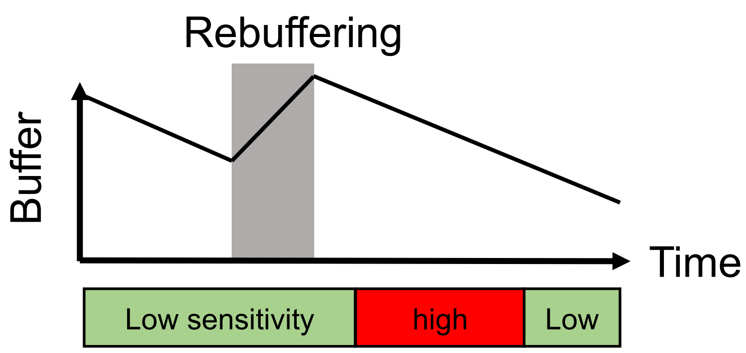
More reliable responses makes higher accuracy of the QoE model

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

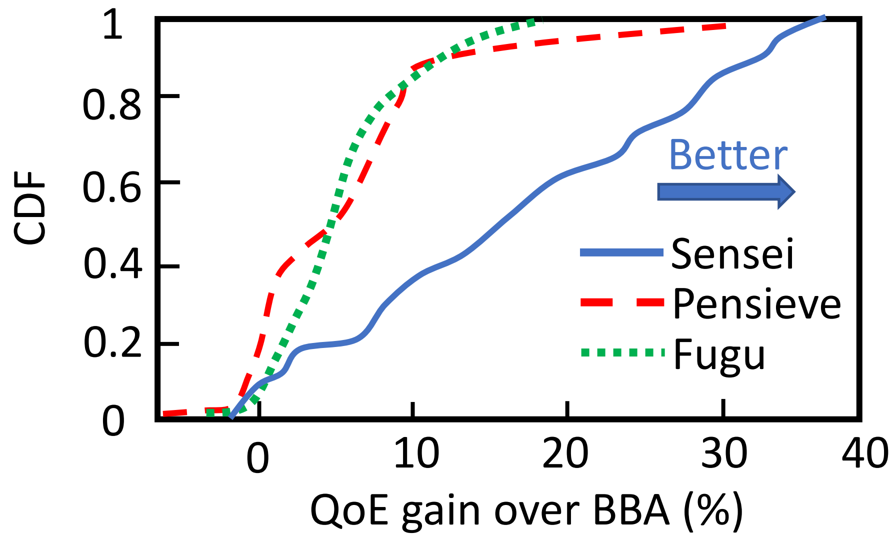
Categories: Animation, Gaming, News, Sports

network throughput traces from FCC and 3G/HSDPA (0.2Mbps – 6Mbps)

Baseline ABR algorithms: Fugu, Pensive, BBA

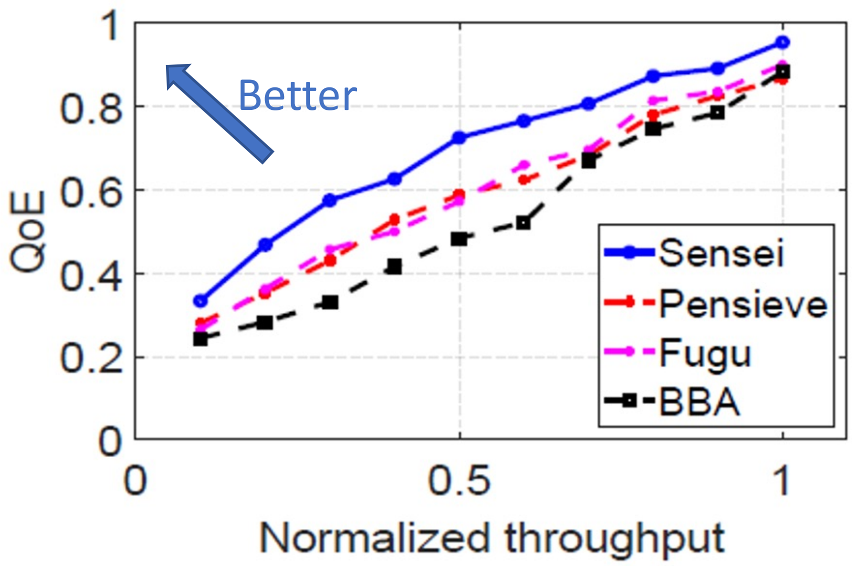
Sensei achieves higher QoE

Sensei has **<u>15.1%</u>** higher QoE under the same bandwidth



Sensei can save bandwidth

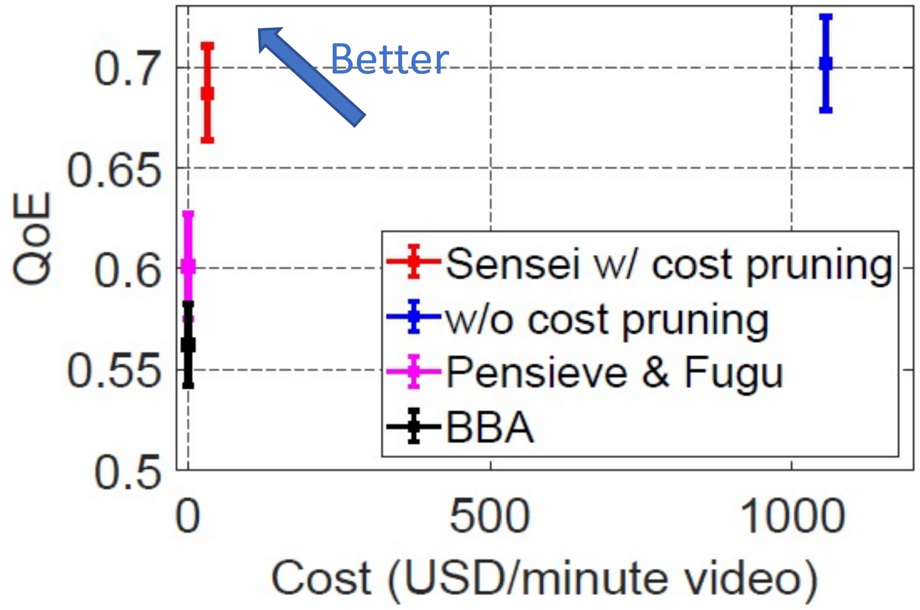
Sensei has **26.8%** less bandwidth usage but the same QoE as other ABR algorithms



Sensei’s cost

Sensei’s cost is **~$31.4** per minute video

Saving **~30x** compared with the crowdsourcing w/o cost pruning



Put more in the paper

Accuracy of Sensei's QoE model

QoE impact by number of crowd workers

Parameter selection for user study

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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,[1] 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 lower

Summary

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