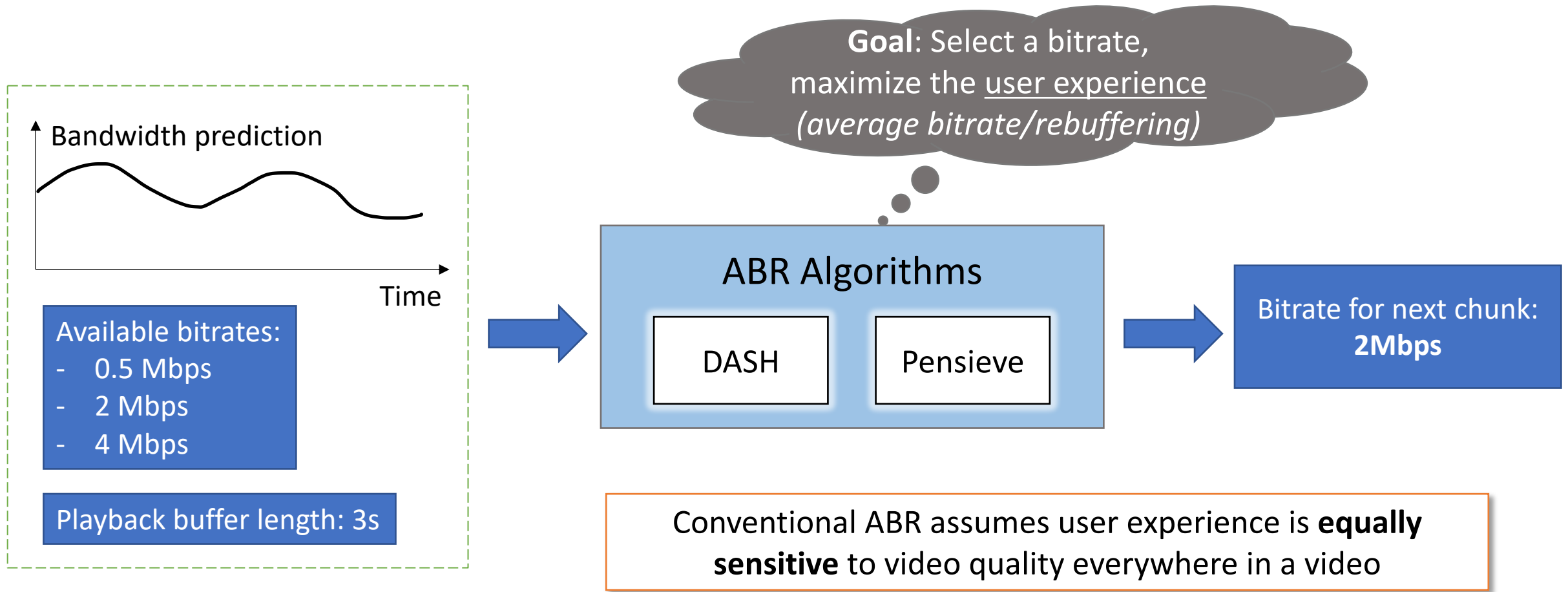# Online Profiling and Adaptation of Quality Sensitivity for Internet Video

Yihua Cheng, Hui Zhang, Junchen Jiang

Resource allocation algorithms in video streaming


Bandwidth prediction

Time

Available bitrates:
- 0.5 Mbps
- 2 Mbps
- 4 Mbps

Playback buffer length: 3s

Goal: Select a bitrate, maximize the user experience *(average bitrate/rebuffering)*

ABR Algorithms

DASH

Pensieve

Bitrate for next chunk: **2Mbps**

Conventional ABR assumes user experience is **equally sensitive** to video quality everywhere in a video

Observation in some videos:
  User's **sensitivity** to bad quality is related to video contents

Observation in some videos:
User's sensitivity to bad quality is related to video contents

Severe bitrate decrease happens at different video chunks.
Which one is worse?

Does such **variation of quality sensitivity** exist in videos **in the wild**?

Content: The player is taking a shot
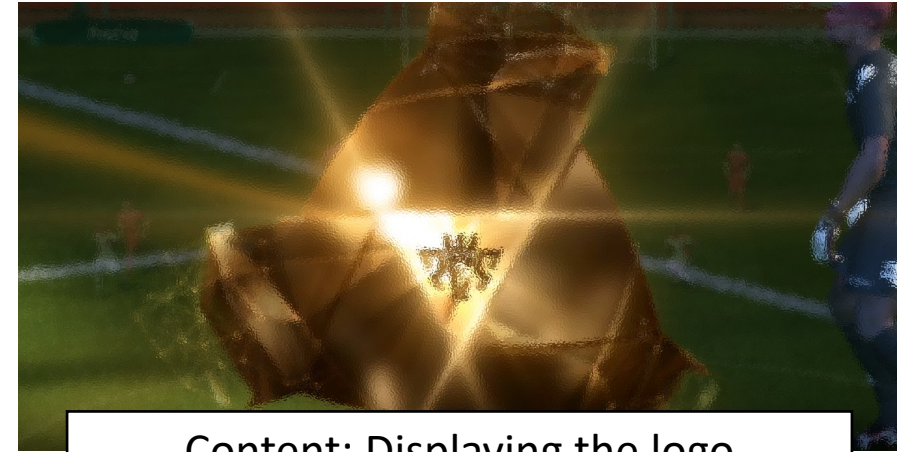
Content: Displaying the logo
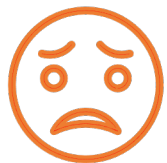
I cannot clearly see what's happening!
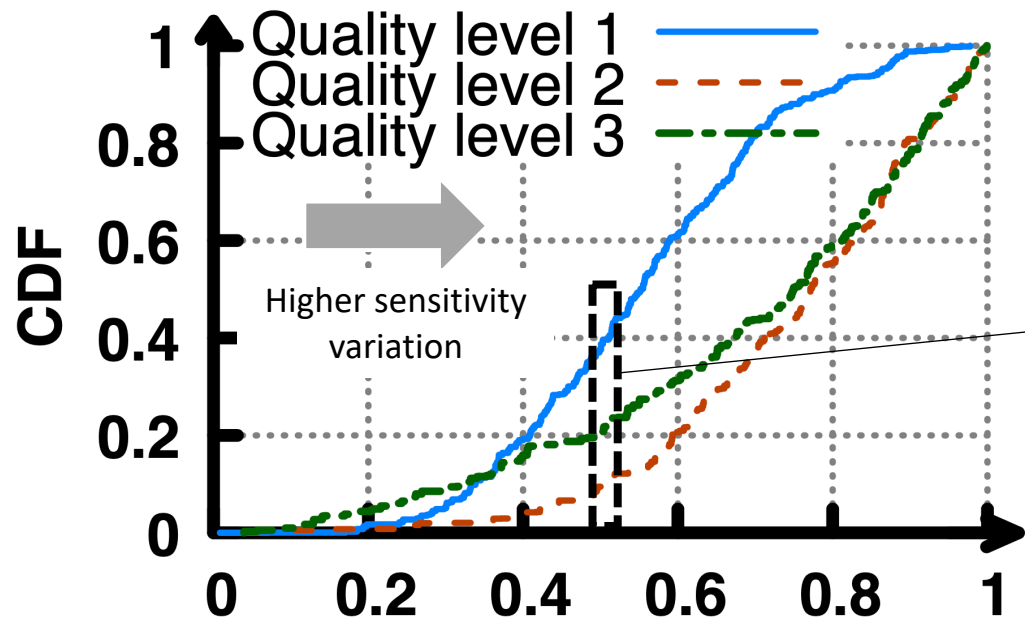
Well, it's just a logo.

Quality sensitivity variation **commonly exists** in all videos

We collected **18 days** of user-side measurement data, including video quality and user actions, from **7.6M session** of **4 popular content providers**, covering **3.09M view hours**

Quality level 1
Quality level 2
Quality level 3

CDF

Higher sensitivity variation

Among all videos, over 60% of 5-chunk windows will have a sensitivity variation larger than 50%

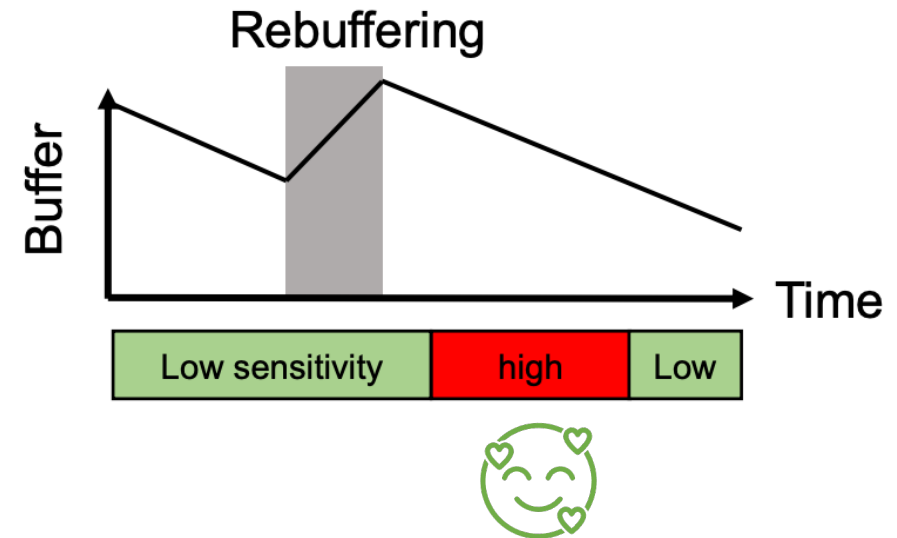$(max - min) / max$ **of quality sensitivity in 5 consecutive video chunks**

High **quality sensitivity** means a higher ratio of users quit the video segment after bad video quality

Quality sensitivity helps improve user experience

Traditional ABR algorithm
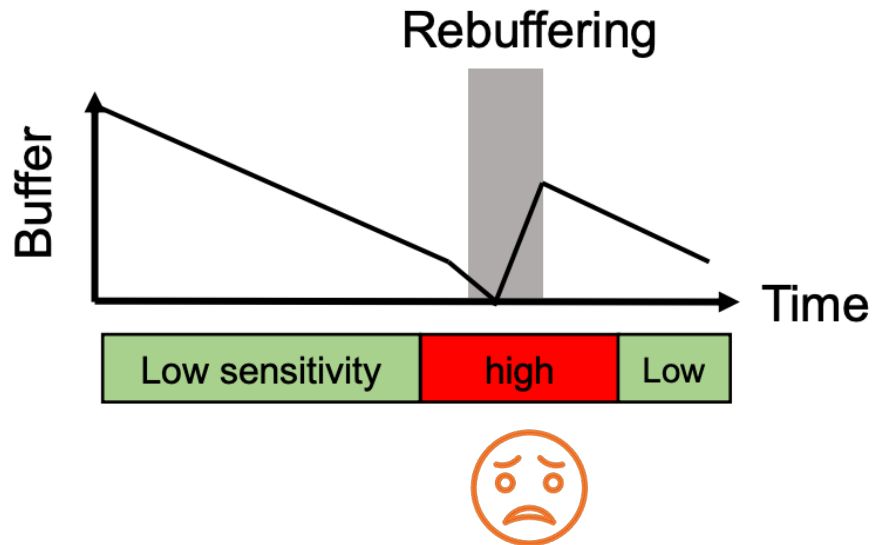
Sensitivity-aware ABR algorithm

Key challenge: estimate the quality sensitivity **accurately** and **quickly**
- **Accurately**: can apply better optimization
- **Quickly**: can benefit more users

Existing methods to estimate quality sensitivity

- **Heuristic-based methods**: use pixel values or viewing history to infer the sensitivity
  - Fast but inaccurate (no real users)

- **Offline survey-based methods**: ask participants to watch and rate the video quality
  - Accurate but too slow *(offline user study takes hours)*!
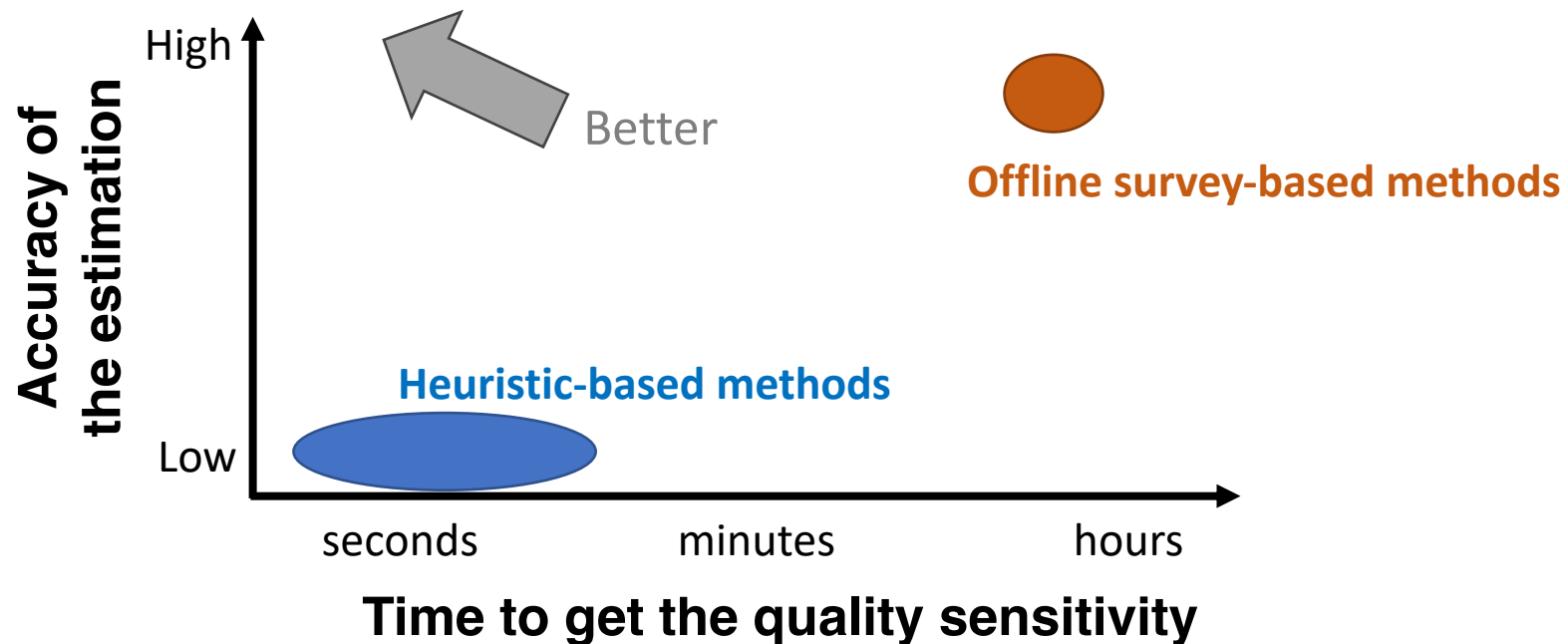
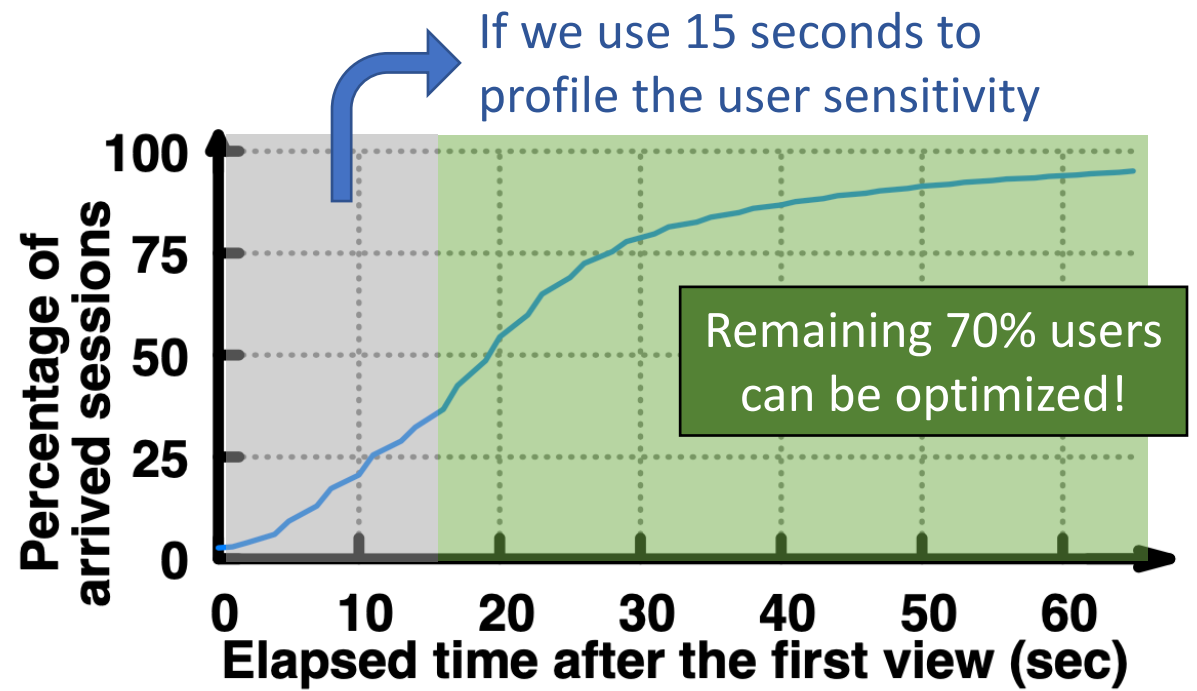# Online quality sensitivity modeling has a better trade-off

- **Our approach (SensitiFlow):** Online collect the early user's feedback to build the quality sensitivity model on the cloud controller, then optimize the later user's QoE
  - As quick as heuristic based methods (*online processing*)
  - As accurate as survey-based methods (*real user actions*)
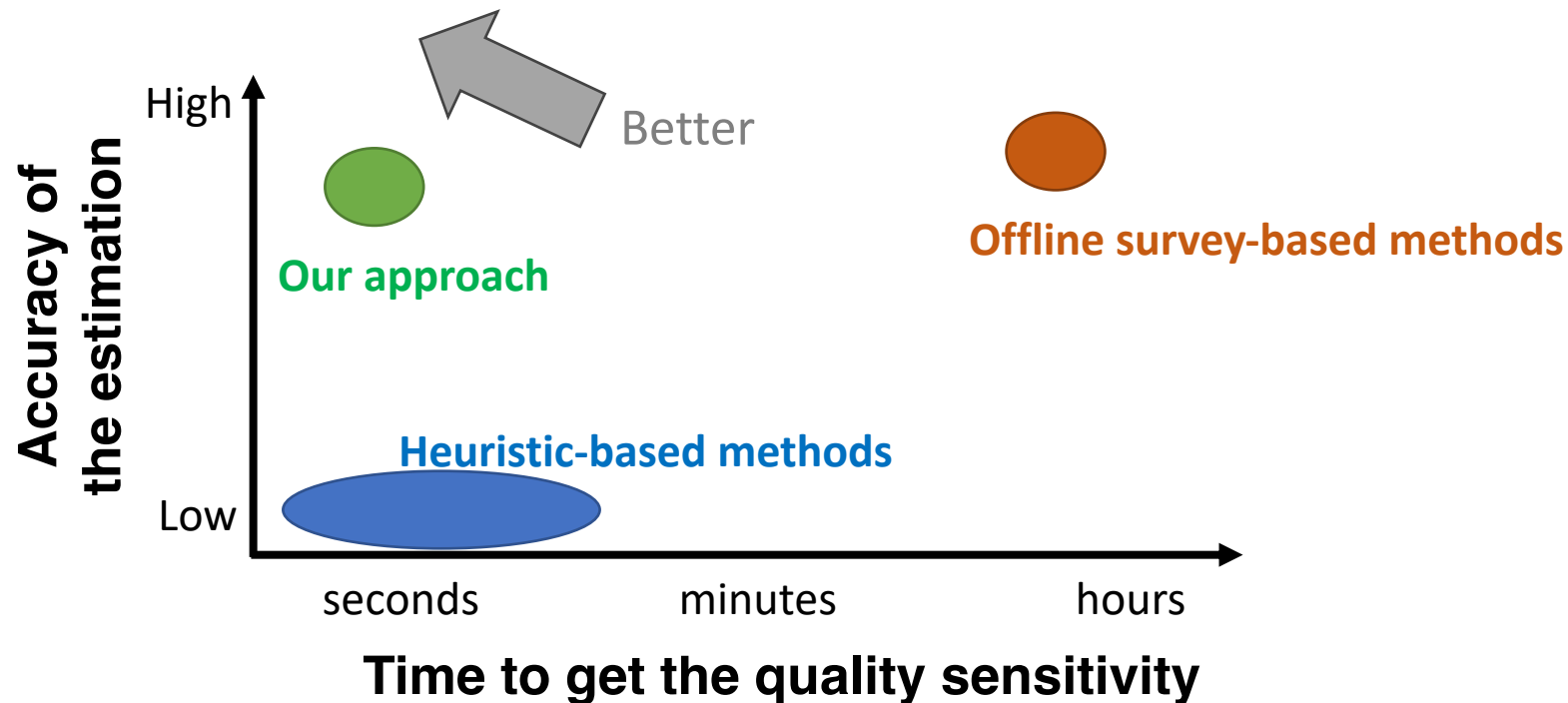
Why SensitiFlow works?

- **Reason 1**: Popular contents have enough viewers to reduce the measurement noises

- **Reason 2**: most views of a live video span up to tens of seconds, providing a window for optimization

Example: a live sports event has ~100K viewers

If we use 15 seconds to profile the user sensitivity

Remaining 70% users can be optimized!

Percentage of arrived sessions

100

75

50

25

0

0   10   20   30   40   50   60

Elapsed time after the first view (sec)

SensitiFlow improves the engagement of users

- Trace-driven simulation experiment
    - Use user arrival traces from 12 live videos, 3 VoD videos
    - Use bandwidth trace from FCC-dataset

FastMPC ▬ Our approach (SensitiFlow) ▬

Normalized engagement gain (%)

Live videos

VoD videos

Achieving X% of the maximum potential gain
obtained by knowing quality sensitivity in advance
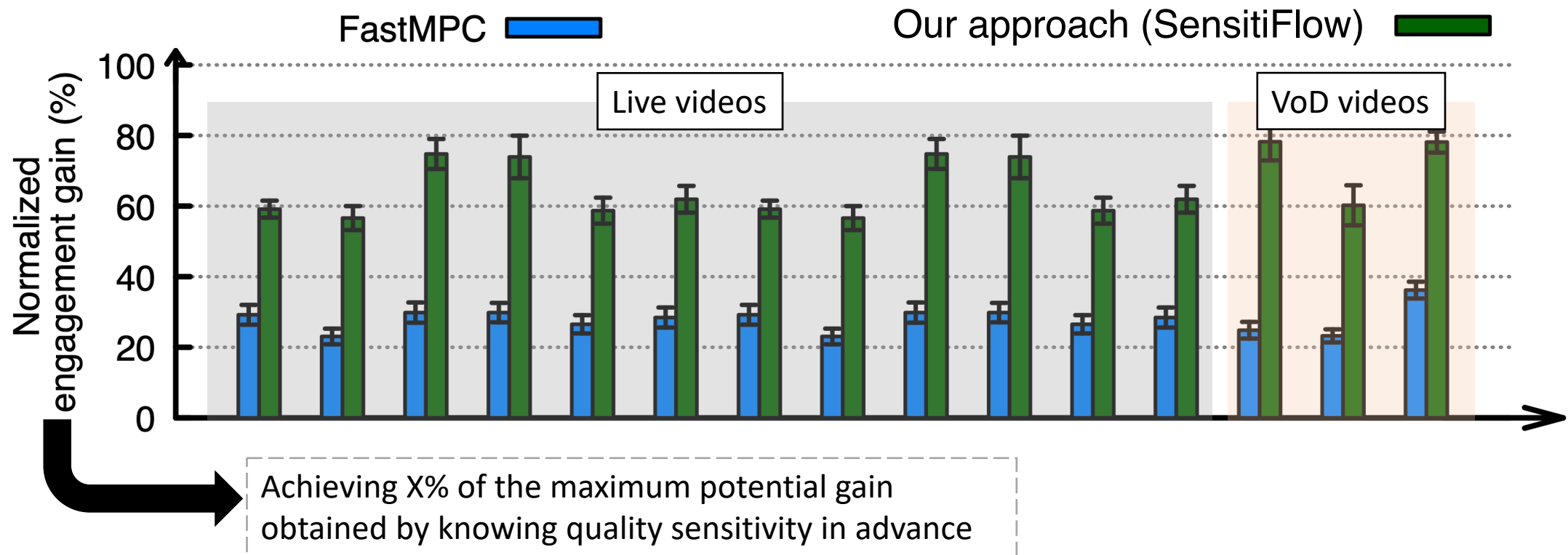
Limitations and future work

- Limitation: Only have a small prototype system, no real-world deployment

- Future work 1: Large-scale system implementation on real-time event processing engine

- Future work 2: real-world A/B test

- Future work 3: extend the idea of "online profiling" to different domains
  - Short video services (such as Tik-Tok)
  - Social media app providers