Building Gamer QoE Models to Adapt Cloud VR Gaming for Optimal User Experience

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Outline

- Motivation
- Goal & Challenges
- System Architecture
- QoE User Study
- QoE Modeling
- Dynamic Adaptations
- Evaluations
- Conclusion & Future Work

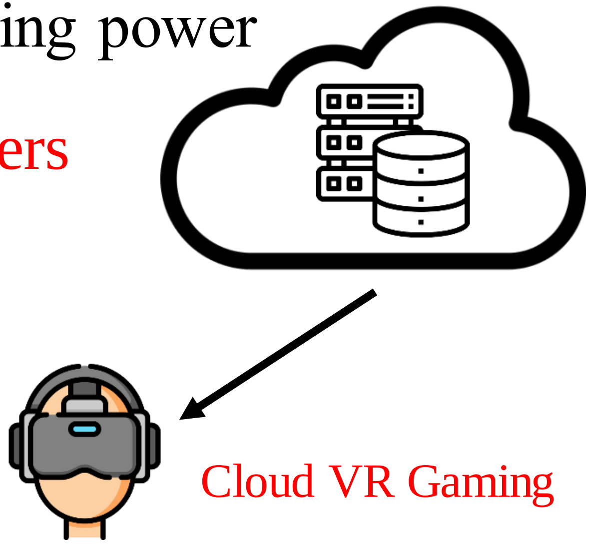
Limitation on Today’s Head-Mounted Displays (HMDs)

- PC-tethered HMDs constrain the mobility of the user
- Standalone HMDs don’t have enough rendering power

★ Offload rendering workload to powerful servers

HTC VIVE

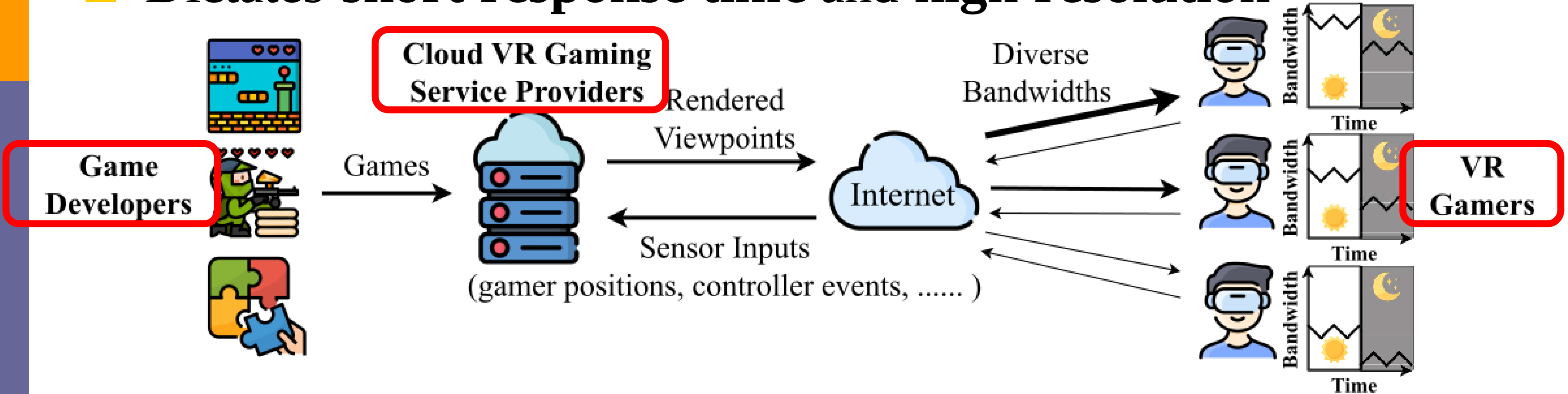
Meta Quest 2



Motivation

Cloud VR Gaming

- Consists of three parties
  - Game developers
  - Cloud VR gaming service providers
  - VR gamers
- Dictates **short response time** and **high resolution**



Motivation

Sample Cloud VR Games

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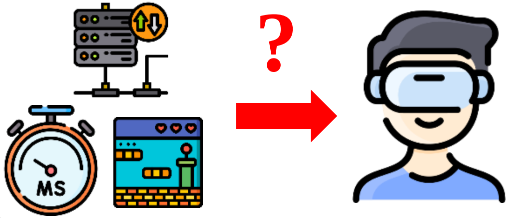
Quality-of-Experience (QoE) Optimization

- Goal: **Design a cloud VR gaming system achieving optimal gamer QoE**
- Challenges:

★ Three steps approach: **QoE evaluations, QoE modeling, QoE-driven dynamic adaptations**

Diverse factors influence gamer QoE



Time-consuming user study to understand gamer QoE

Non-trivial adaptations in dynamic systems

Contributions

Traditional cloud gaming, Local Area Network (LAN) VR gaming → **Wide Area Network (WAN) cloud VR gaming**

- Build a cloud VR gaming testbed and **carry out comprehensive QoE evaluations using a user study**
- Construct cloud VR gaming QoE models based on the user study to **predict gamer QoE** The **very first models** built for cloud VR gaming systems
- Develop a QoE-driven adaptation algorithm to **adapt the encoding settings dynamically for maximizing gamer QoE**

QoE-driven adaptation in cloud VR gaming hasn't been investigate before

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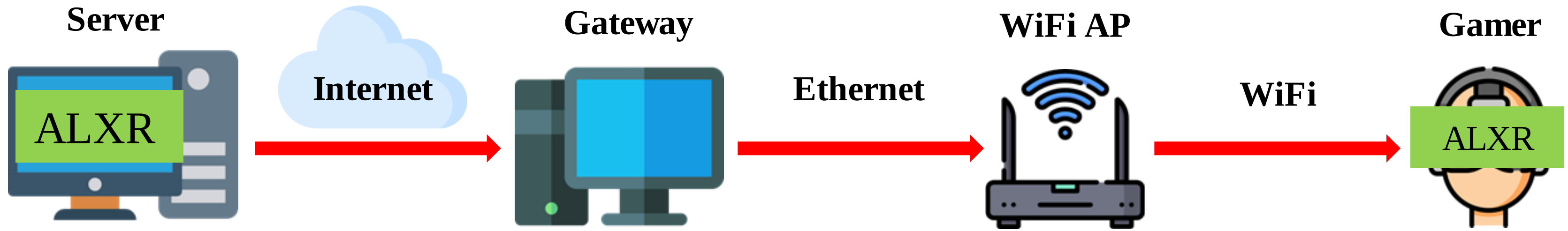
Cloud VR Gaming Platform

★ We chose ALXR as the starting point of our cloud VR gaming platform:
(i) It is a fully open-source platform
(ii) It supports more HMD models

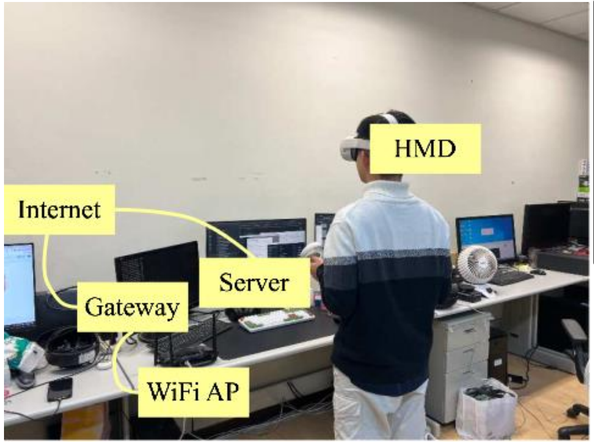
- NVIDIA CloudXR
  - Only the client side is open-sourced
  - Both wired and wireless streaming are supported
  - Both local and remote rendering are supported
- Air Light VR (ALVR) / Air Light XR (ALXR)
  - Fully open-sourced
  - Only supports wireless streaming
  - Only works in LAN settings We make it to support WAN

Our Cloud VR Game Streaming System



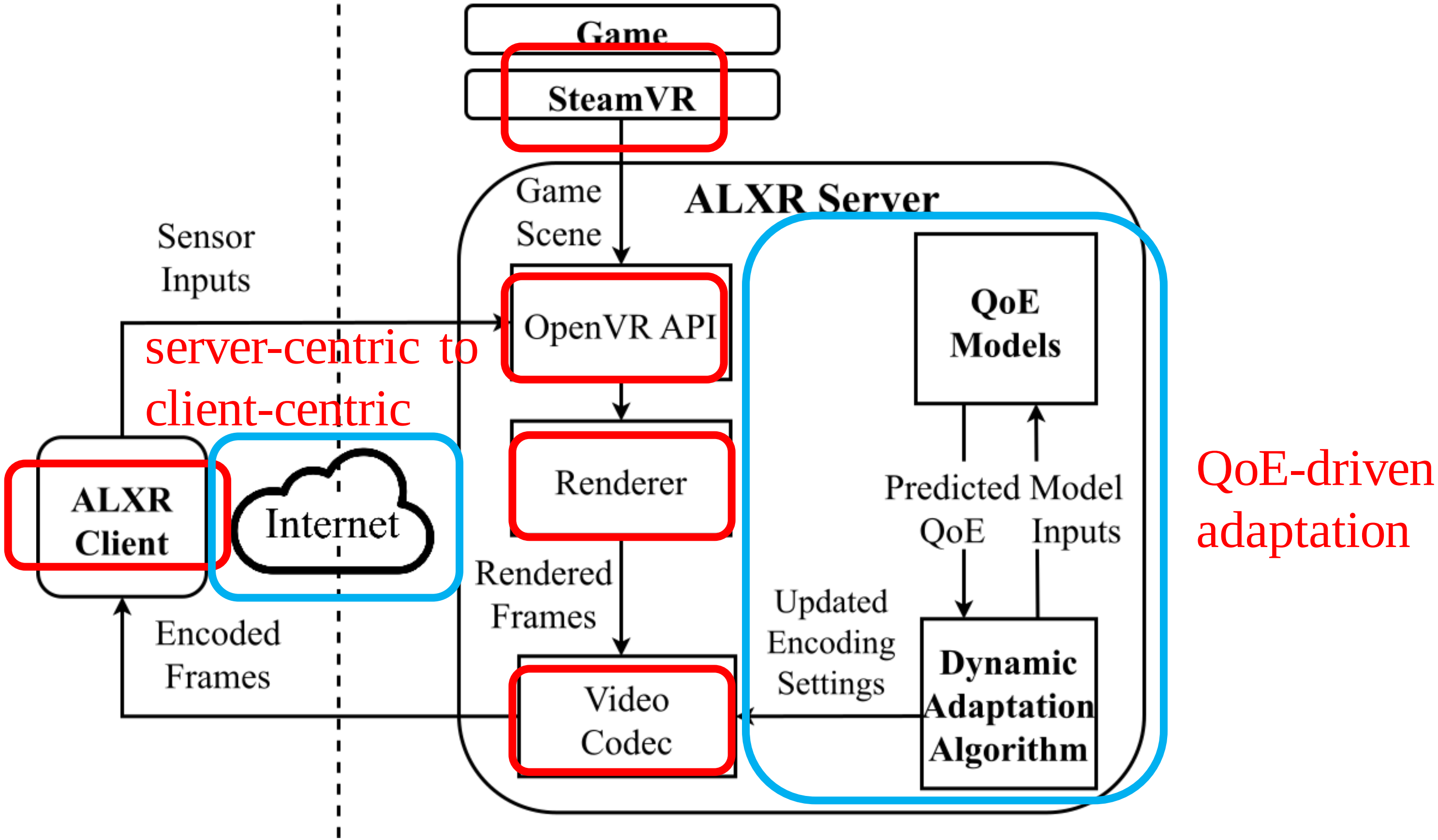
Frame Renderer

Network Emulator (Bandwidth, Delay, …)



Display

ALXR Architecture



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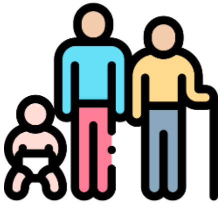
Quality-of-Experience (QoE)

- Subjective assessment of an individual's overall satisfaction and perception of the quality of a service or application
  - System factors (ex: bandwidth, delay, ……)
  - Context factors (ex: task types, surrounding environments, ……)
  - Human factors (ex: age, gender, ……)

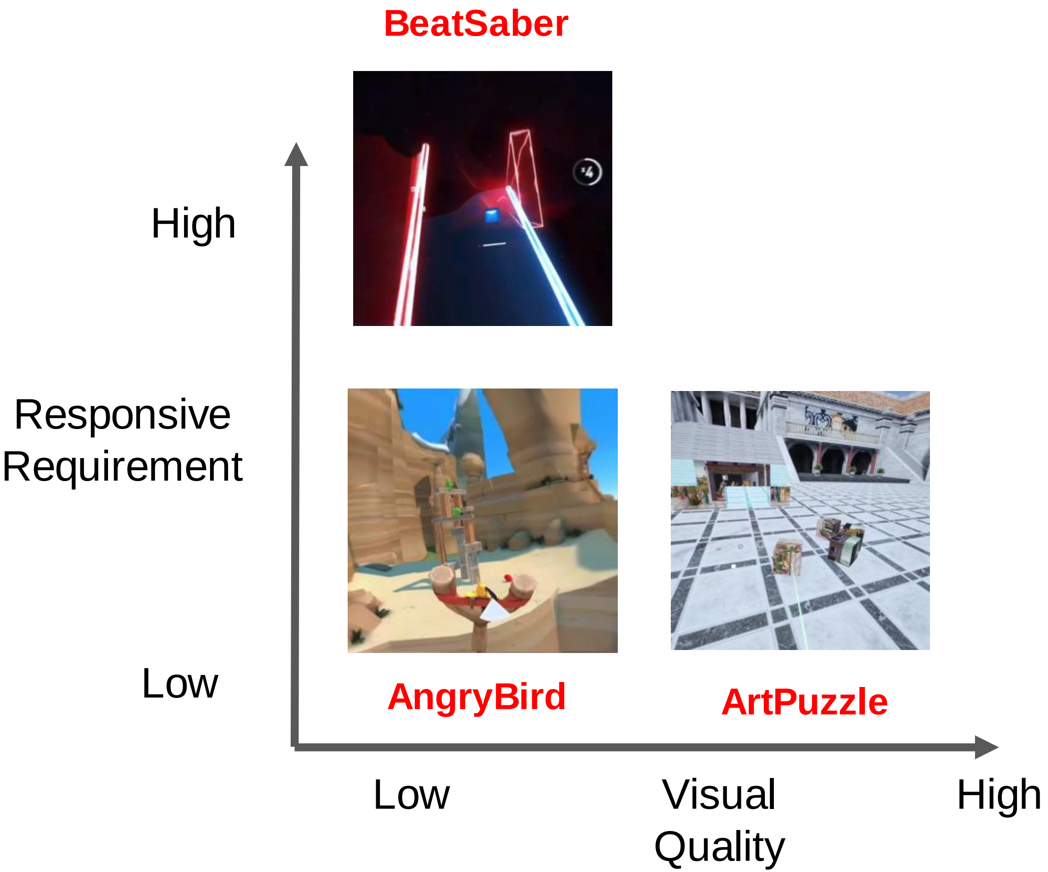


Why User Study?

- Understand the gamer QoE under the influence of different factors, including diverse:
  - Game genres
  - Encoding settings
  - Network conditions
- The user study results can be utilized for building QoE models

Games in the User Study

- Leisure game
  - AngryBird
- Time-sensitive game
  - BeatSaber
- Quality-sensitive game
  - ArtPuzzle



QoE User Study

Experimental Setup

24 sessions

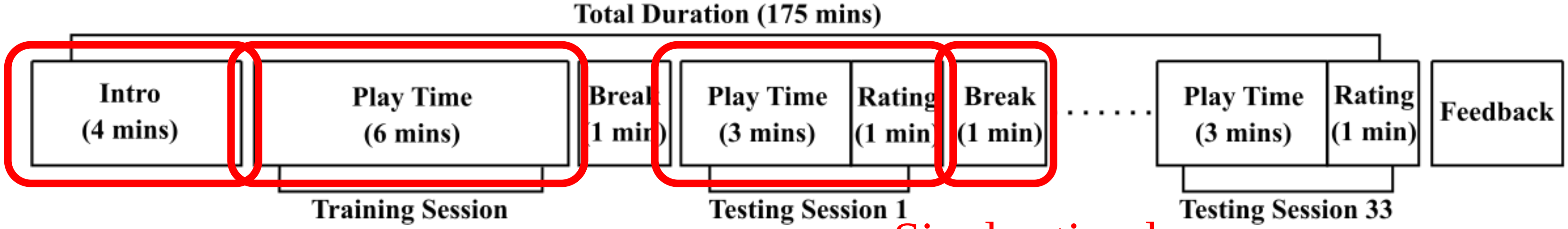
- Different encoding settings
  - Bitrate: {2, 8, **32**} Mbps
  - Frame rate: {12, 24, 36, **72**} fps
  - Resolution: {1408x768, 2112x1184, **2880x1568**}
- Different network conditions
  - Delay: {**0**, 100, 300, 500} ms

9 sessions

QoE	Rating
Overall Quality	1 (Bad) – 5 (Excellent)
Visual Quality	1 (Bad) – 5 (Excellent)
Immersive Level	1 (Low) – 5 (High)
Cybersickness	1 (No problem) – 5 (Unbearable)
Continue	0 (No) – 1 (Yes)

Absolute Category Rating (ACR)

★ Each subject undergoes 33 sessions (12 subjects)



Single stimulus

Considered Objective Metrics

- Networking metrics
  - Throughput
  - Packet loss rate
  - Delay
  - Frame loss rate
- Video quality metrics
  - Peak Signal-to-Noise Ratio (PSNR)
  - Structural Similarity Index (SSIM)
  - Video Multimethod Assessment Fusion (VMAF)

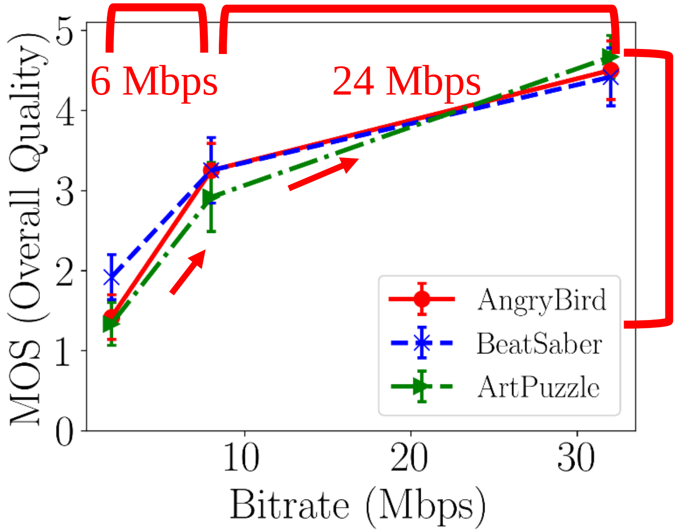
★ Inputs for QoE modeling

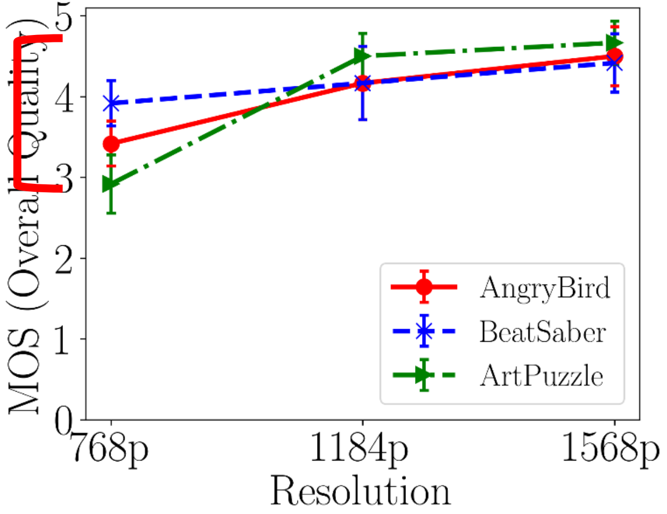
We use the default 1080p HDTV screen model of VMAF

1. Key Control Knob: Bitrate

- Bitrate affects the gamer QoE the most among other settings
- Mean Opinion Score (MOS) growth rate decelerates as bitrate increases

★ Bitrate needs to be carefully considered



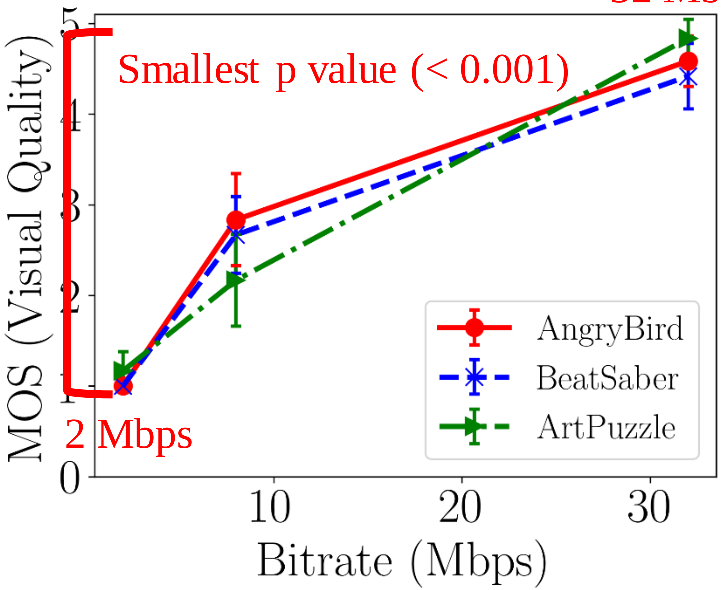


★ Game genres affect gamer QoE

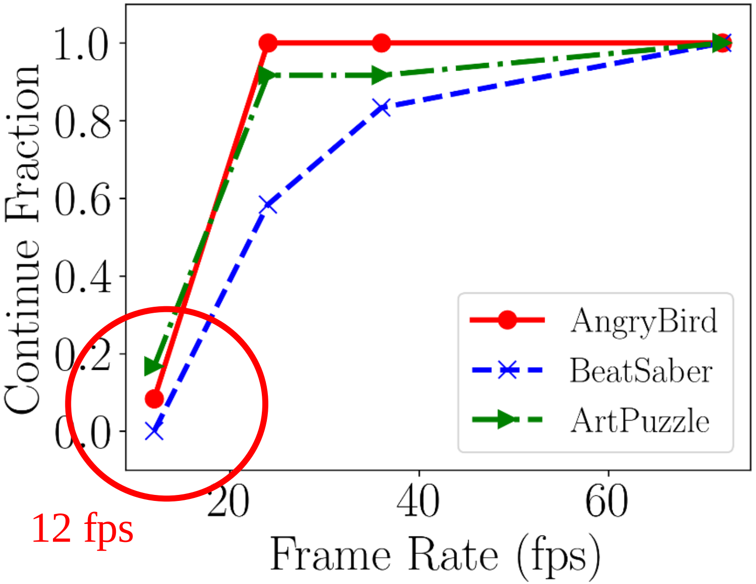
2. Different Game Genres Have Different Requirements

- Art puzzle is more sensitive to bitrate changes
- Beat saber is more sensitive to frame rate changes

32 Mbps



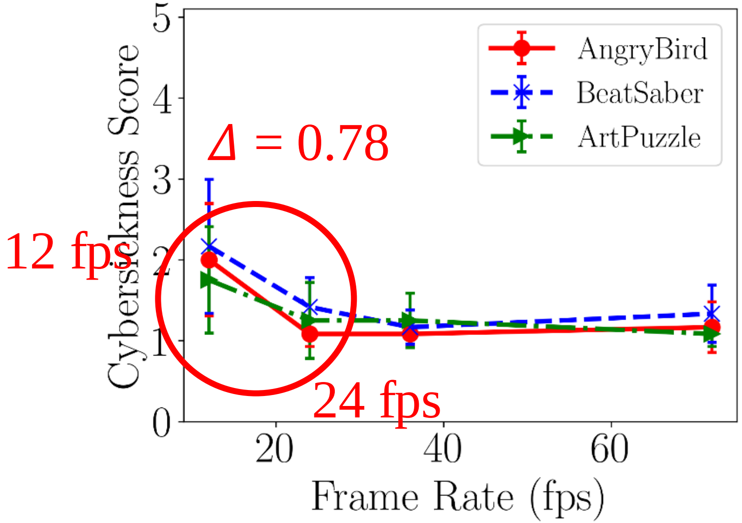
2 Mbps

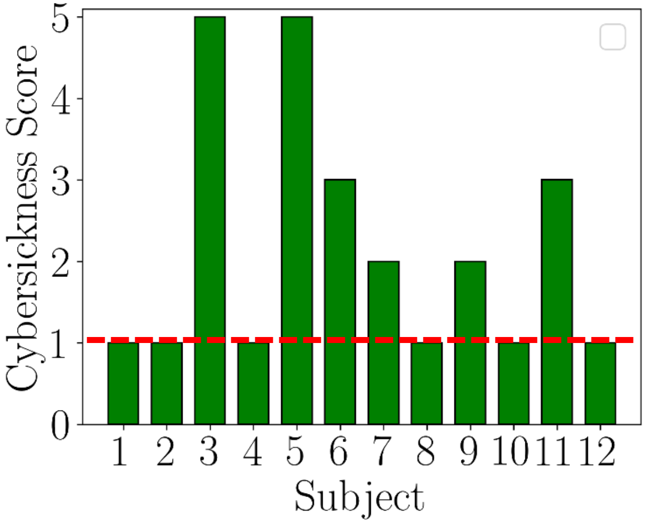


12 fps

3. Cybersickness Highly Depends on Subject

- Significant changes only occur when frame rate < 24 fps
- Some subjects are comfortable even under extreme settings, e.g., 12 fps ★ We leave modeling cybersickness as future work





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Modeling Methodology: Inputs & Outputs

- System Factor
  Encoding Settings
  - Bitrate / Frame rate / Resolution
  - Throughput / Delay / Packet loss rate / Frame loss rate Network Conditions
  - PSNR / SSIM / VMAF
  Video Quality Metrics
- Content Factor
  - Game genres (SI / TI)

  Spatial Information / Temporal Information
- Human Factor
  - VR experience No / Yes
  - Gaming experience
  Naive, Intermediate, Advanced

Modeling Methodology: Models & Metrics

- Regression models
  - Random Forest (RF)
  - Gradient Boosting (GB)
  - Ada Boosting (AB)
  - Polynomial (Poly)

- Metrics
  - R^2 (0 ~ 1) ⬆
  - PLCC (-1 ~ 1) ⬆
  - SROCC (-1 ~ 1) ⬆

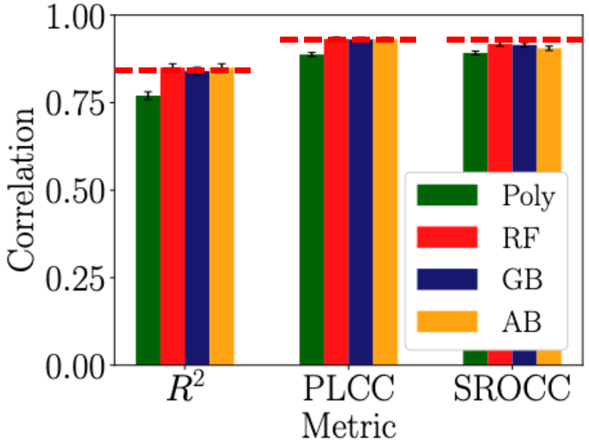
★ We split the user study results by subjects and conduct 3-fold cross-validations

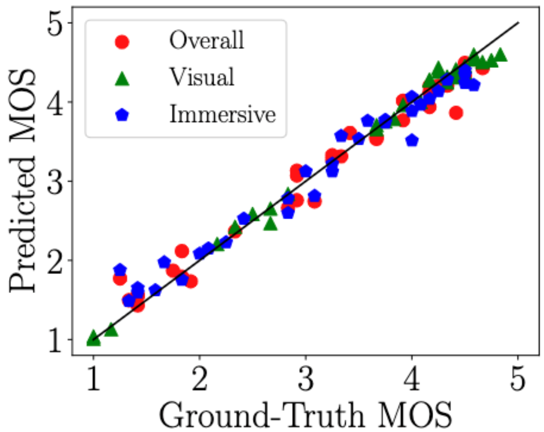
Random Forest Performs the Best

- We train the model in two ways
  - Per-game models w/o game genres
  - General models Use SI/TI to represent game genres

Max $\Delta R^2 = 0.02$

- Random forest achieves **up to 0.85 in R^2, 0.93 in PLCC, and 0.92 in SROCC**





Lightweight Models for Dynamic Adaptations

- Some model inputs are measured with external tools
  - Frame loss rate
  - PSNR
  - SSIM
  - VMAF

★ We exclude these inputs and trained lightweight models

$Q_O \rightarrow \tilde{Q}_O \quad Q_V \rightarrow \tilde{Q}_V \quad Q_I \rightarrow \tilde{Q}_I$

- The performance gaps between original and lightweight models are **at most 0.02 in R^2, 0.01 in PLCC, and 0.02 in SROCC**

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Problem Formulation

- For each adaptation, **find the best encoding settings e*** that leads to the highest QoE

★ We consider overall quality $\tilde{Q}_O$ for concrete discussions

$$e^* = \underset{e=(b,f,r)}{argmax}\ \tilde{Q}_O(\boxed{b, f, r,}\ \ldots)$$

Bitrate, Frame rate, Resolution

$$\text{s.t. } (1+\alpha)b \leq B.$$

15%

- α denotes the overhead
- B denotes the available bandwidth

Faced Challenges

- QoE evaluations are time-consuming → **cannot try too many encoding settings**
- Measured inputs, throughput, delay, and packet loss rate scatter across large ranges → **huge search space**
- Numerically optimal algorithms take excessive running time → **bad for real-time cloud gaming**

Our Solution Approach

- Adopt quadratic function to interpolate encoding settings that were not in the user study → **increase the considered encoding settings**
- Discretize the range of each measured input into multiple bins → **lower the search space**
- Construct a lookup table $\hat{Q}_O$ from $\tilde{Q}_O$ to search for e^* → **reduce (actually, eliminate) run time complexity**

QoE-driven Adaptation (QDA) Algorithm

bitrate	Frame rate	……	Throughput	Delay	……	MOS
32	36	……	24	50	……	3.67
32	60	……	30	20	……	4.15
⋮	⋮	⋮	⋮	⋮	⋮	⋮

genres and search for e^* in the lookup table $\hat{Q}_O$

★ Overhead of QDA algorithm is < 20ms

★ QDA is executed every δ seconds

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Technical Setup

★ Bandwidth lower than 3 Mbps is excluded

- Real 5G network traces [1]
  - Bandwidth is dedicated to **one client (C1)**
  - Bandwidth is equally divided among **five clients (C5)**
  - Bandwidth is equally divided among **ten clients (C10)**
- Baselines
  - No adaptation (NA)
  - Delay threshold-based adaptation (DTA) → ALXR's adaptation

[1] Darijo Raca, Dylan Leahy, Cormac J Sreenan, and Jason J Quinlan. 2020. Beyond throughput, the next generation: a 5G dataset with channel and context metrics. In Proc. of ACM Multimedia Systems Conference (MMSys). Istanbul, Turkey, 303–308.

Demo Videos


NA
alxr_client
Resume
Quit


DTA
alxr_client
Resume
Quit


QDA
alxr_client
Resume
Quit

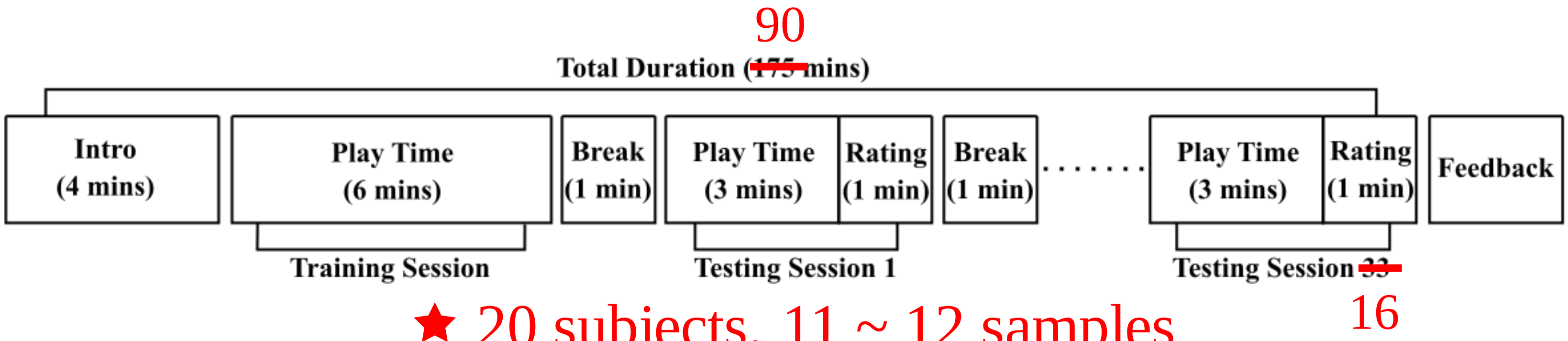
Test Methods

- ~~33~~ 27 gaming sessions
  - 3 game genres
  - ~~8 encoding settings + 3 network conditions~~

  → 3 adaptation algorithms, 3 network conditions

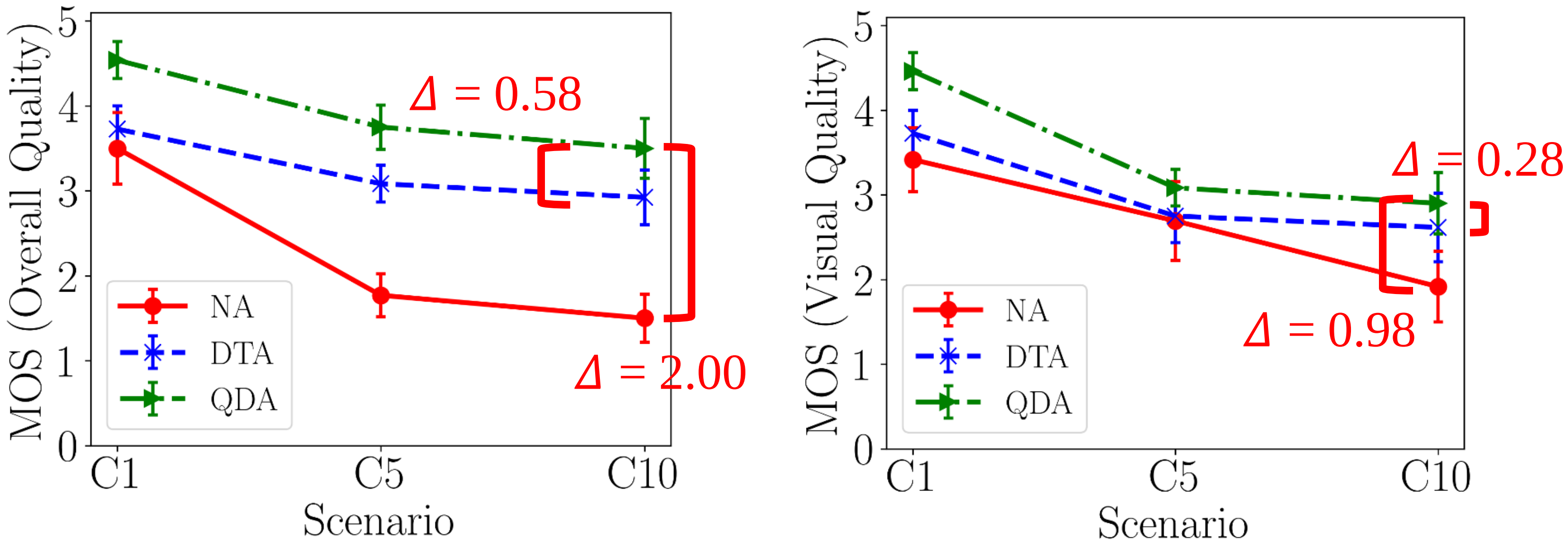
QoE	Rating
Overall Quality	1 (Bad) – 5 (Excellent)
Visual Quality	1 (Bad) – 5 (Excellent)
Interaction Quality	1 (Not Responsive) – 5 (Completely Responsive)
Cybersickness	1 (No problem) – 5 (Unbearable)

subject Absolute Category Rating (ACR)



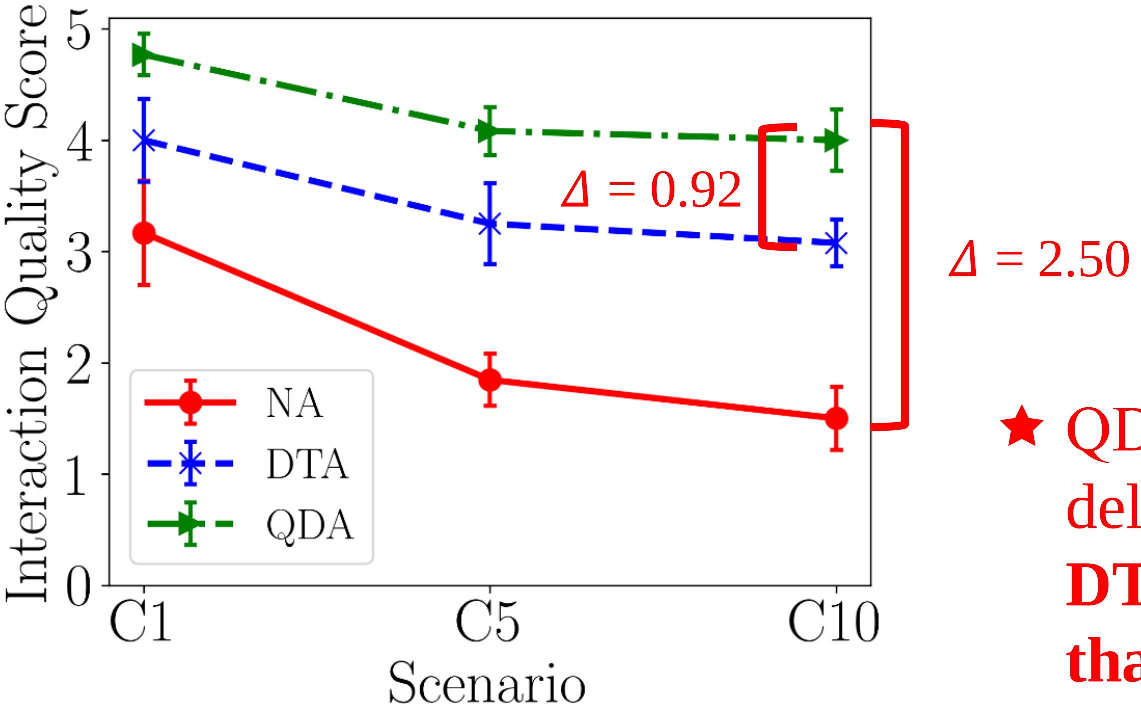
★ 20 subjects, 11 ~ 12 samples for each scenario

1. QDA Achieves the Best Quality in MOS



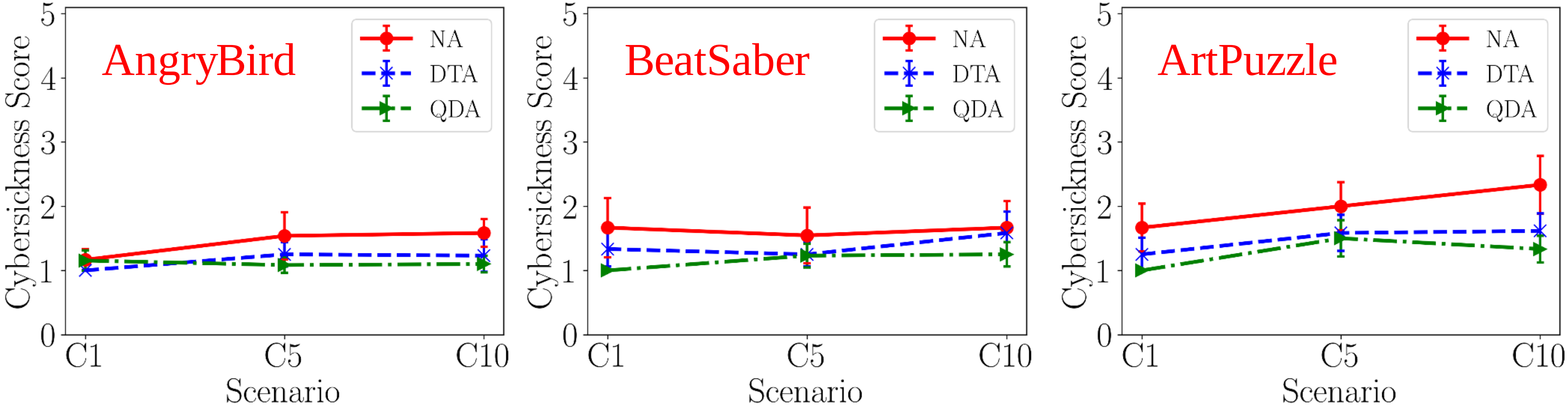
★ QDA's packet loss rate is **7.59% lower than DTA and 24.56% lower than NA**

2. QDA Demonstrates the Highest Responsiveness



★ QDA's round-trip network delay is **3 ms lower than DTA and 3.5 ms lower than NA**

3. QDA Reduces the Cybersickness Score



★ QDA's cyberscкness score is 0.34 lower than DTA and 0.63 lower than NA on average

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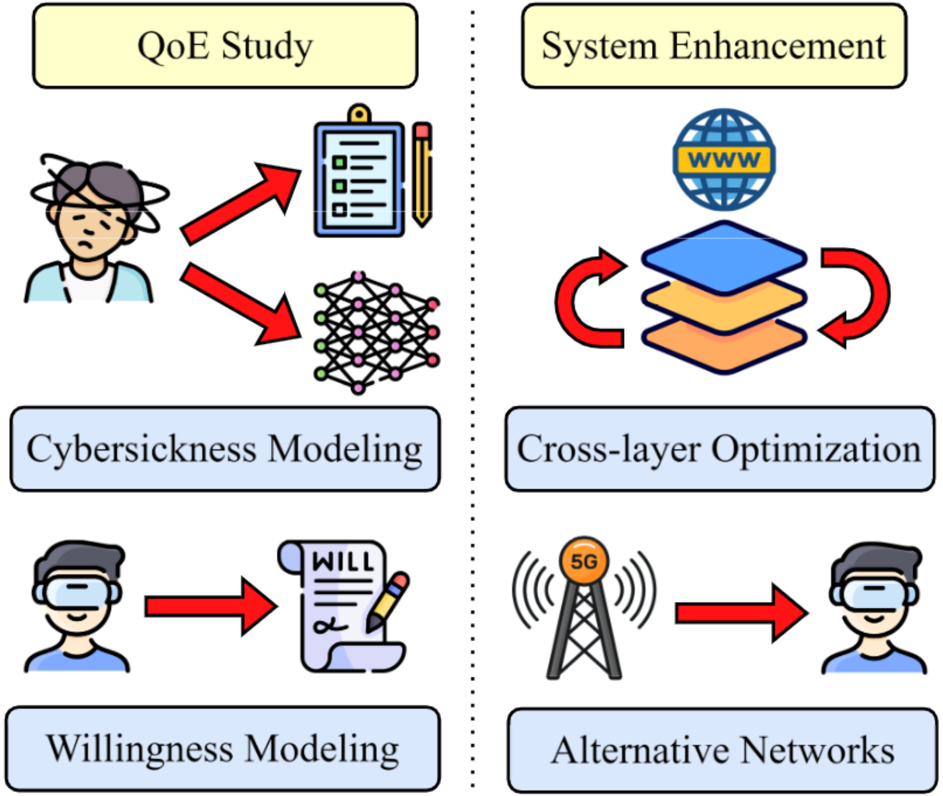
Conclusion

- Constructed a cloud VR gaming system and conducted comprehensive QoE evaluations
- Built QoE models that achieve up to:
  - **0.93 in PLCC**
  - **0.92 in SROCC**
- Developed QoE-driven adaptation algorithm which:
  - Improved the MOS of overall quality by up to **1.86** on average across three game genres
  - Reduced cybersickness score by up to **0.63** on average across three game genres

Future Directions

More Human Factors

QoS Metrics



Radio Information Network Service (RNIS)

5G Fixed Wireless Access (FWA) / Cellular Network

Thank you for listening

Thank for the help of Dr. Ashutosh Singla (CWI), Dr. Pablo Cesar (CWI), Jia-Wei Fang, Yuan-chun Sun and all lab mates.

Publications:

[1] K. Lee, A. Singla, P. Pablo, and C. Hsu. 2024. Adaptive cloud VR gaming optimized by gamer QoE models. ACM Transactions on Multimedia Computing, Communications, and Applications (Under Review)

[2] K. Lee, J. Fang, Y. Sun, and C. Hsu. Modeling gamer quality-of-experience using a real cloud VR gaming testbed. In Proc. of ACM International Workshop on Immersive Mixed and Virtual Environment Systems (MMVE’23). Vancouver, Canada, June 2023, pp. 12–17.

[3] J. Fang, K. Lee, T. Kamarainen, M. Siekkinen, and C. Hsu. Will dynamic foveation boost cloud VR gaming experience? In Proc. of ACM International Workshop on Network and Operating Systems Support for Digital Audio and Video (NOSSDAV’23), Vancouver, Canada, June 2023, pp. 29–35.

[4] S. Tang, Y. Sun, J. Fang, K. Lee, C. Wang, and C. Hsu. Optimal camera placement for 6 degree-of-freedom immersive video streaming without accessing 3D scenes. In Proc. of ACM International Workshop on Interactive Extended Reality (IXR’22), Lisbon, Portugal, October 2022, pp. 31–39.