



Optimal Strategies for Live Video Streaming in the Low-latency Regime

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Video-over-Ideal-5G

Application
Transport
Network
Data Link
Physical

24K, 360 Degree, Volumetric



AR/VR/MR

Live/Interactive



↑

Higher Throughput: Gbps

↑

Lower Latency, 1ms



Video-over-5G: real challenges

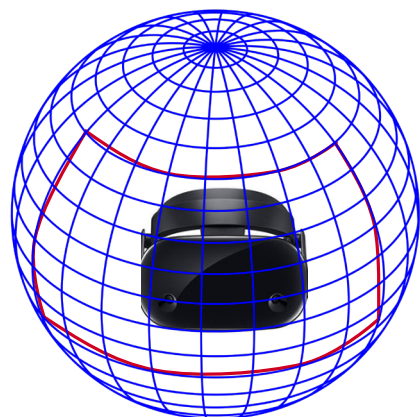
Application Layer	User QoE Optimization with Realistic Network Assumptions
Transport	❖ Users sensitive to video quality and temporal variation
Network	❖ Video freezes/skips/black-screen detrimental to user QoE ❖ Long end-to-end video delay kills interactivity
Data Link	❖ Users want mobile/wireless video
Physical	??? Consistently High-throughput/Low-delay from Lower Layers ???



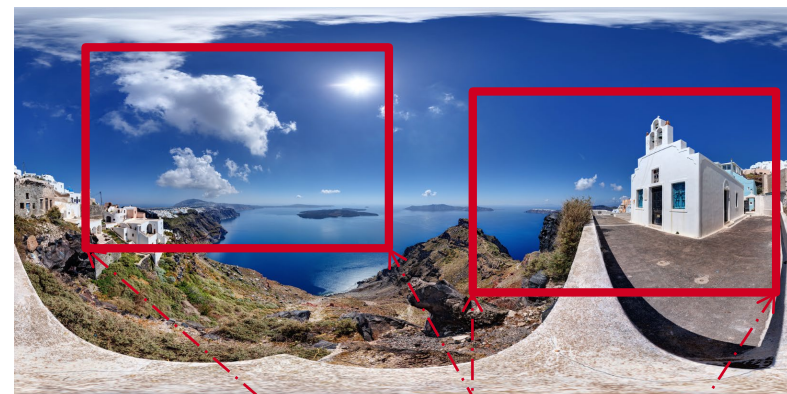
360-degree Video Streaming Projects (joint with Yao Wang)

I. Two-tier on-demand 360° video streaming

- Field-of-View (FoV) streaming to reduce b.w. requirement (1/6)
- two-tier segment coding/streaming to be robust against b.w. and FoV dynamics



Fraction of area within FoV: $120^\circ/360^\circ \times 90^\circ/180^\circ = 1/6$





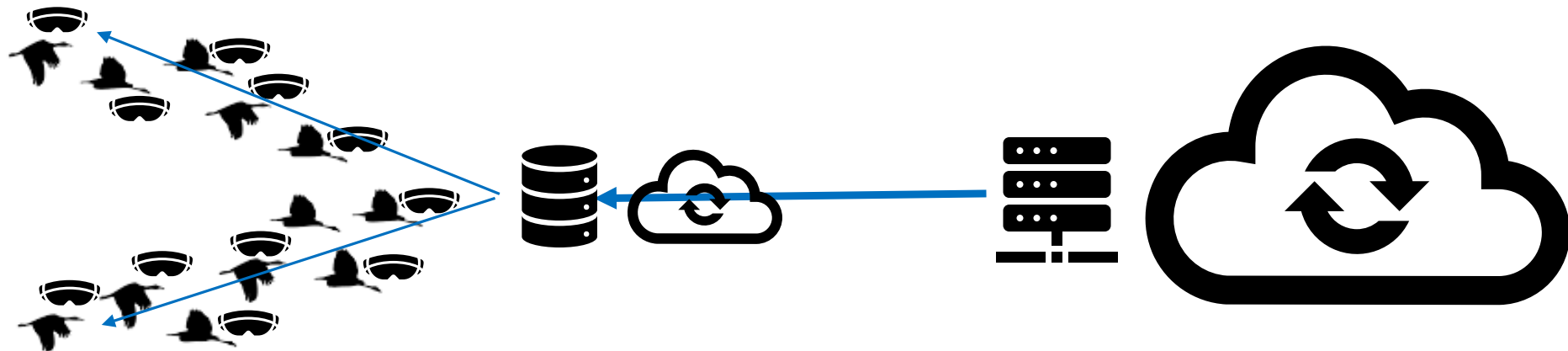
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2. Flocking-based live 360° streaming from edge cloud

- users watching same live event form a “flock”
- users with shorter video lag lead flock: **populating cache, generating realtime “saliency” map**





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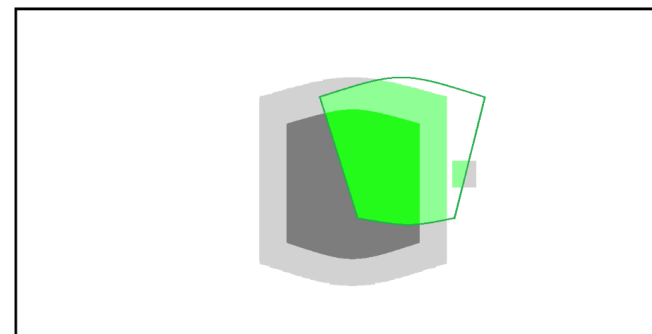
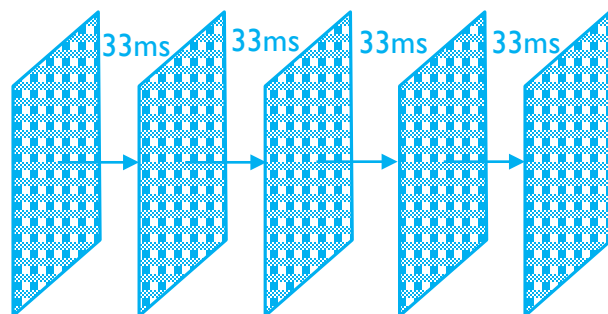
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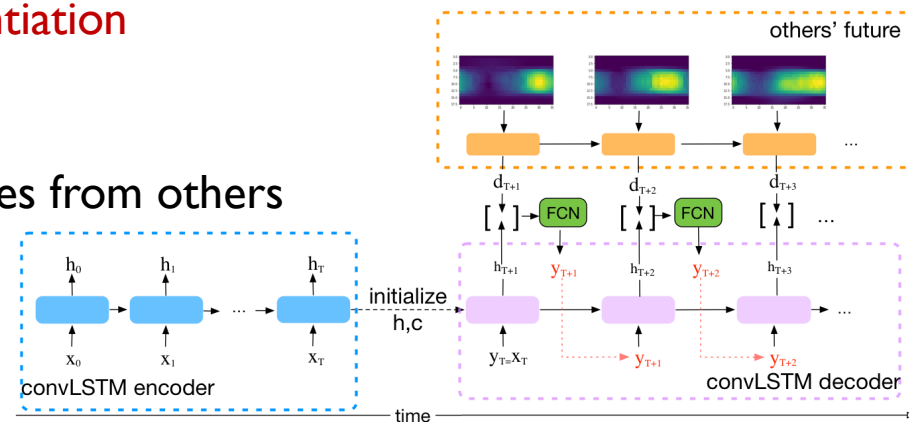
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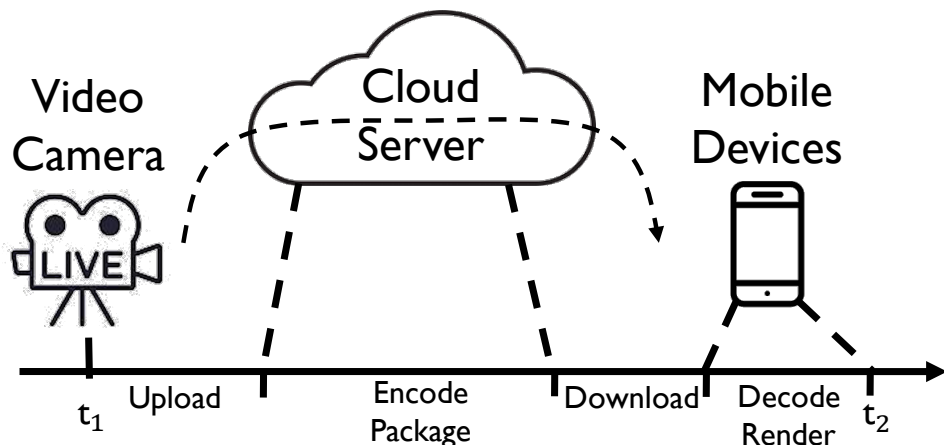
4. Deep-learning based user FoV prediction

- target user past FoV trajectory, and “**future**” trajectories from others
- video content saliency map





Low Latency Live Streaming



Application	Latency (s)
YouTube Live*	7-11
Facebook Live*	~15
Twitch*	~15
FOX, abc**	~7

*: Online Live Streaming

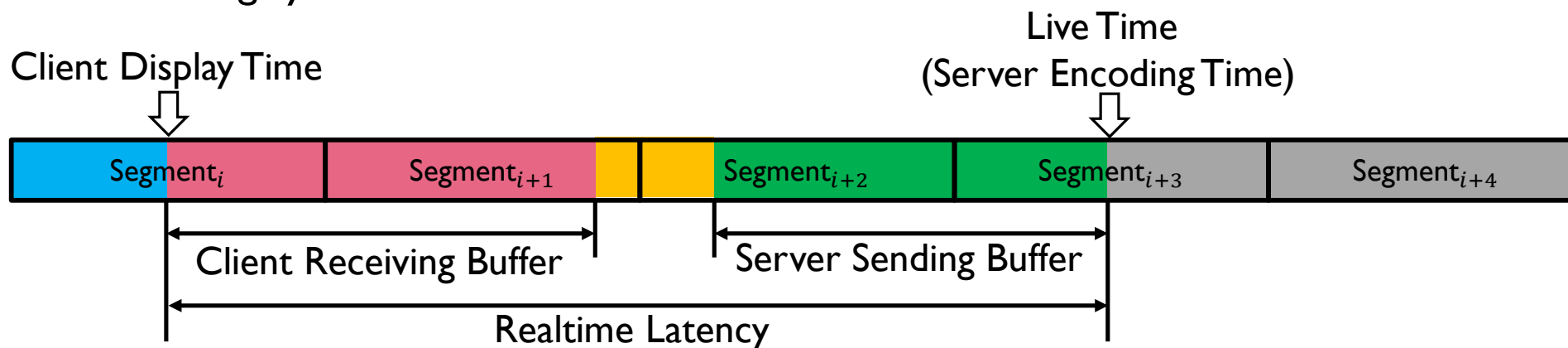
** :TV broadcasting

- Sports, online gaming broadcast, social live UGC,
- Online live streaming still lags behind TV.
- User live/interactivity experience is ruined by long latency!
- **Can we simply shorten latency in live streaming system? No!**



Low Latency and Buffer Length

- Live streaming system state at time T

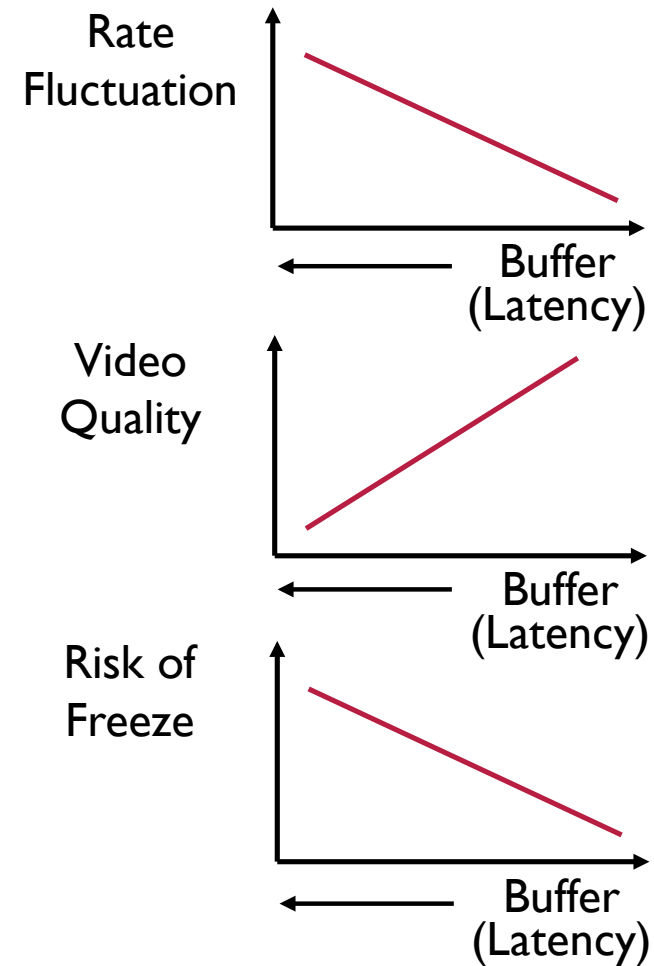
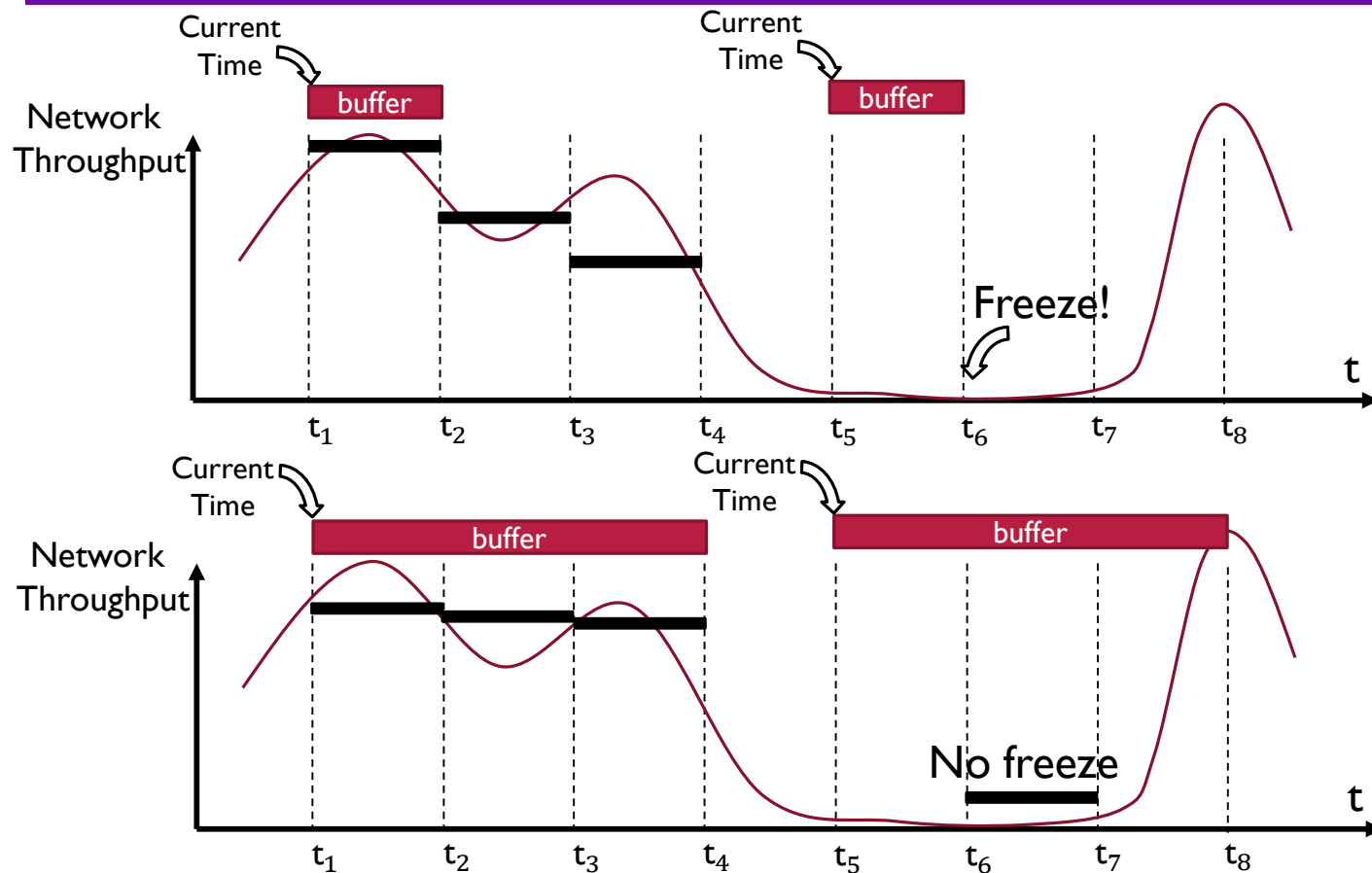


- Video is going to happen in future.
- Video has already been downloaded but not decoded/rendered.
- Video has already been decoded/rendered.
- Video is being transmitted on the network.
- Video has already been encoded to be download.

- Realtime latency is the **upper bound** of client buffer length.



Influence of Buffer Length (Latency)



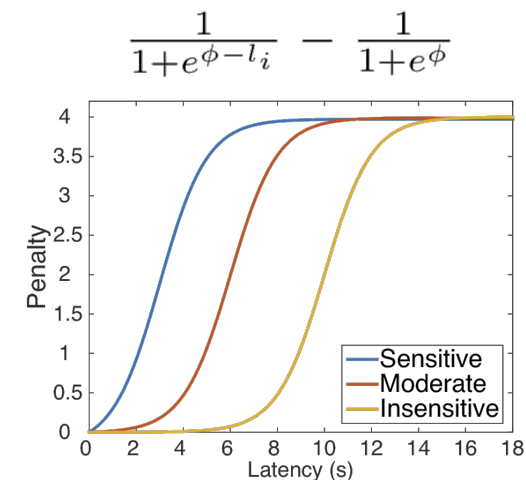
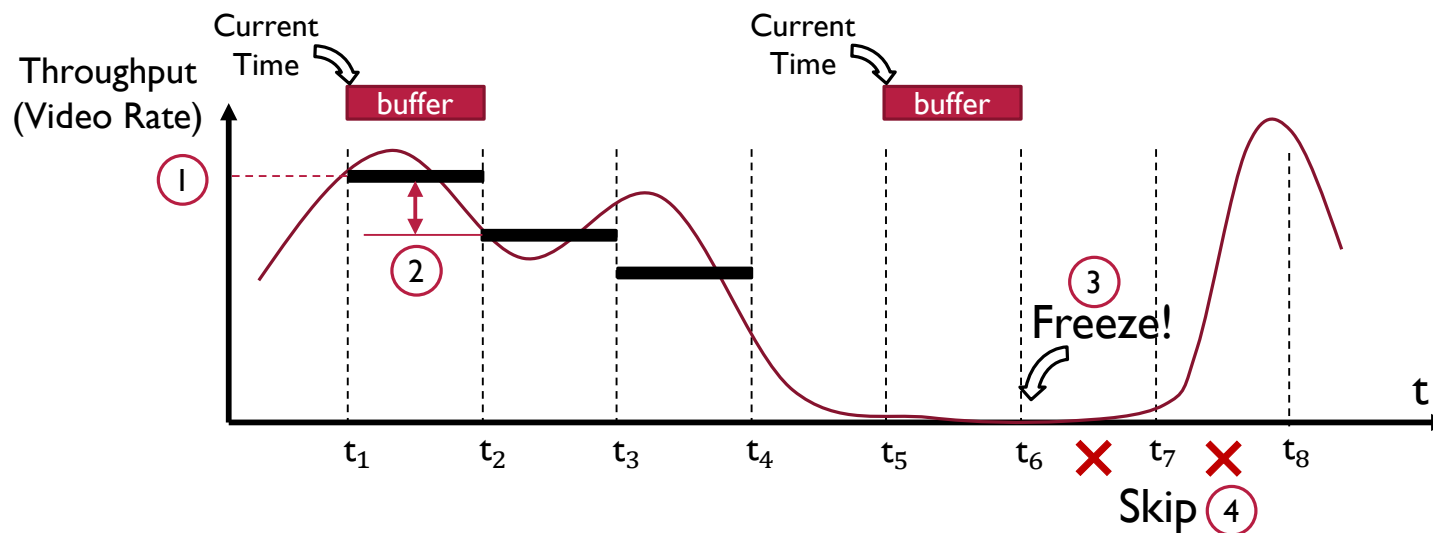
- Shortening latency **negatively impact** all the other QoE metrics.
- Goal: Trade-off between latency and other metrics to maximize QoE.



Live Streaming QoE

- QoE Metrics:

$$QoE = \underbrace{a_1 Q(r_i)}_{\text{① Video Rate}^+} - \underbrace{a_2 |Q(r_i) - Q(r_{i-1})|}_{\text{② Rate Fluctuation}^-} - \underbrace{a_3 x_i}_{\text{③ Freeze}^-} - \underbrace{a_4 n_i}_{\text{④ Skip}^-} - \underbrace{a_5 g(l_i)}_{\text{⑤ Latency}^-}$$

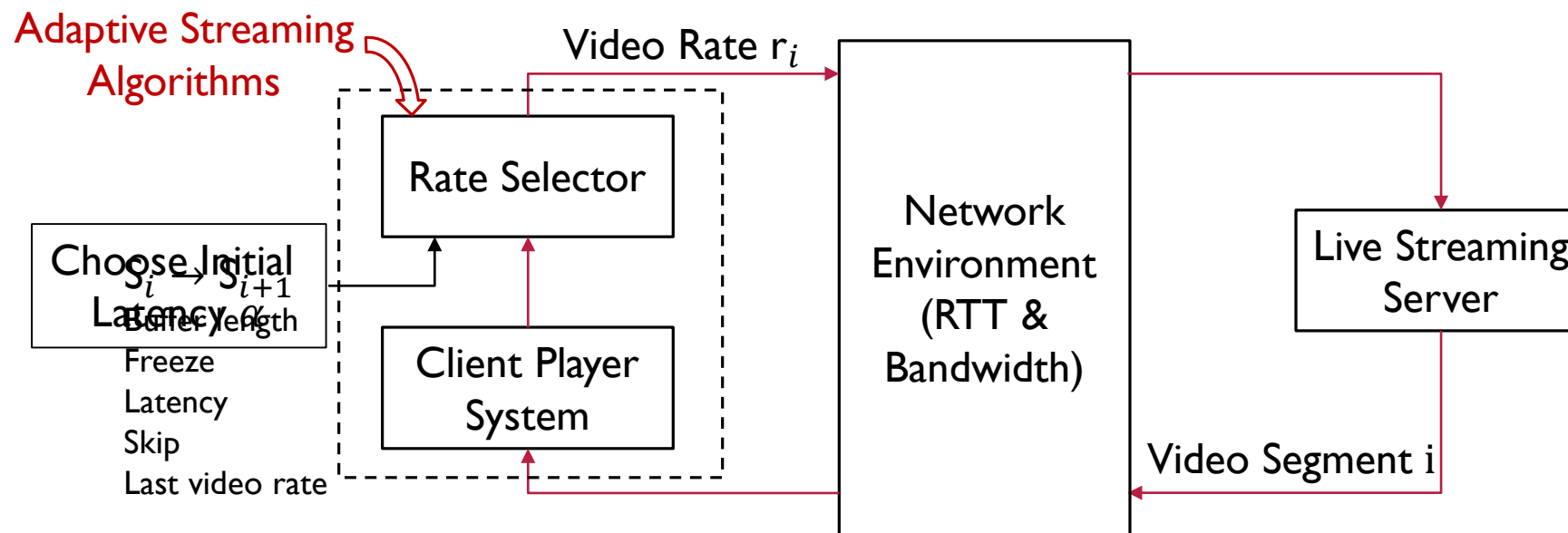




Model of Live Streaming System

- System Evolution

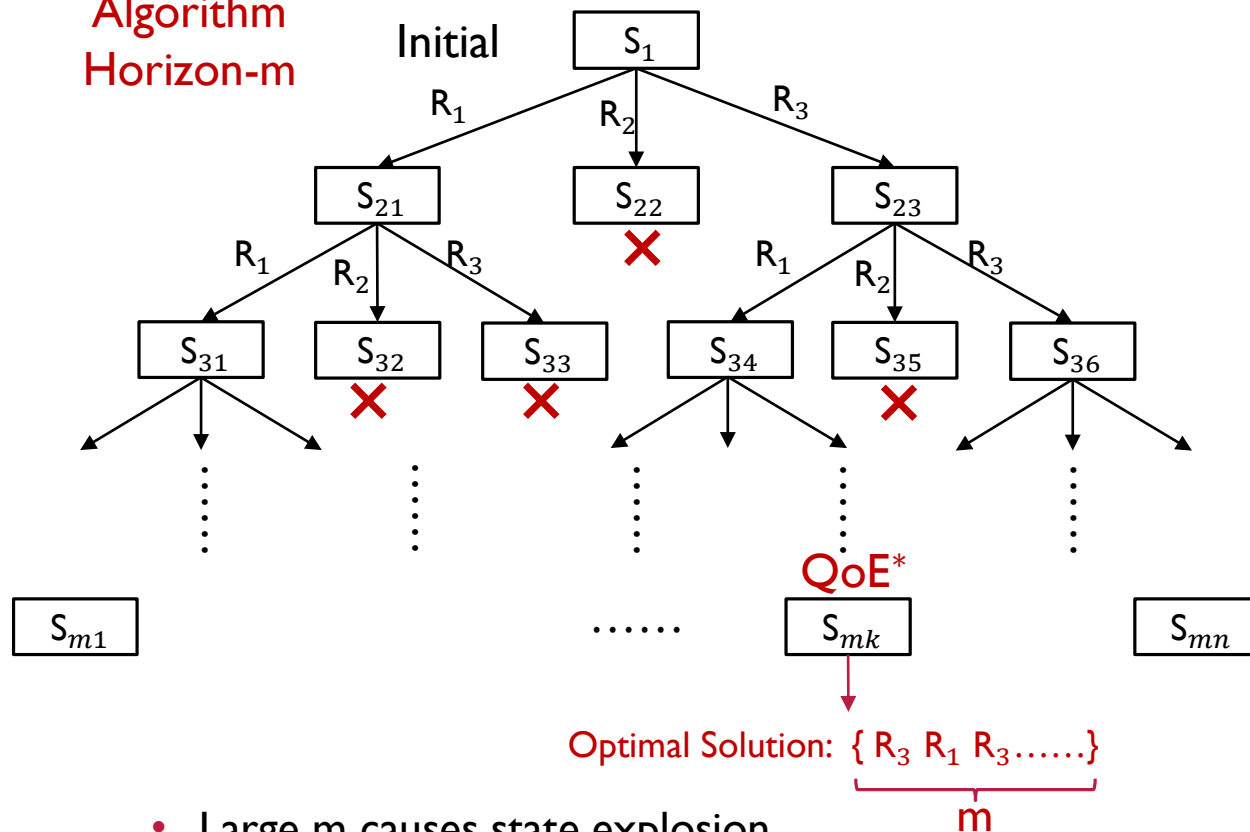
Choose Initial Latency → Choose Rate → Download → Update System State → Choose Rate ...



Optimal Streaming with Network Oracle

- Network condition for future m steps is available.

Algorithm Horizon-m



- Large m causes state explosion.

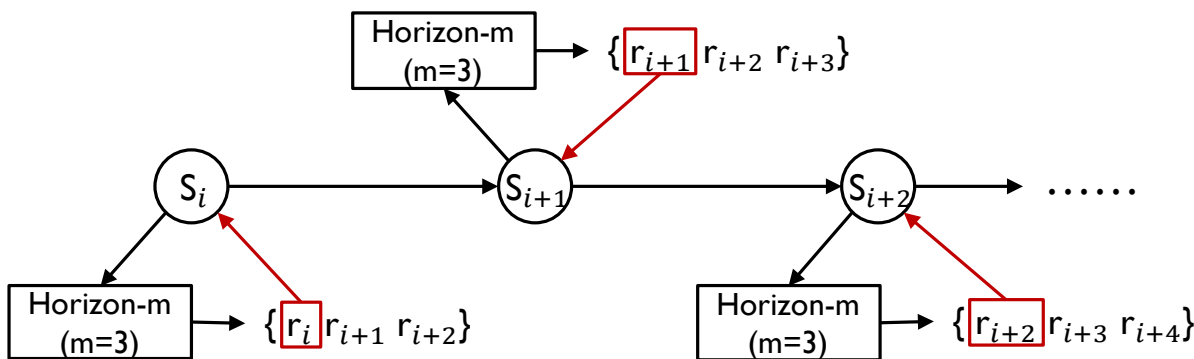
Algorithm 1 Optimal Streaming for Horizon-m

Input: S_1 : the initial state; m : look-ahead horizon; $\{w_i, rtt_i, i \in [1, m]\}$: future available bandwidth and rtt; \mathcal{R} : available rates;
Output: $\{r_i^*, i \in [1, m]\}$: optimal rate sequence.

Initialization: The possible states at stage 1: $\Omega_1 = \{S_1\}$.

- 1: *Branch-and-Bound State Expansion*
- 2: **for** each segment $i \in [1, m]$ **do**
- 3: $\Omega_i = \emptyset$
- 4: **for** each state S in Ω_{i-1} **do**
- 5: **for** each $R_j \in \mathcal{R}$ **do**
- 6: $S'_i = f(S, R_j, \{w_i, rtt_i\})$
- 7: **if** S'_i could be part of the overall optimal solution **then**
- 8: $\Omega_i \leftarrow \Omega_i \cup S'_i$
- 9: **end if**
- 10: **end for**
- 11: **end for**
- 12: **end for**
- 13: Find Optimal Transition $S_1 \xrightarrow{r_1^*} S_2^* \in \Omega_2 \cdots \xrightarrow{r_{m+1}^*} S_{m+1}^* \in \Omega_{m+1}$ to maximize accumulated QoE $\sum_{i=1}^m QoE(S_i, r_i)$ through DP.
- 14: **return** $r_{[1, \dots, m]}^*$

Sliding Window with Horizon-(Small m)

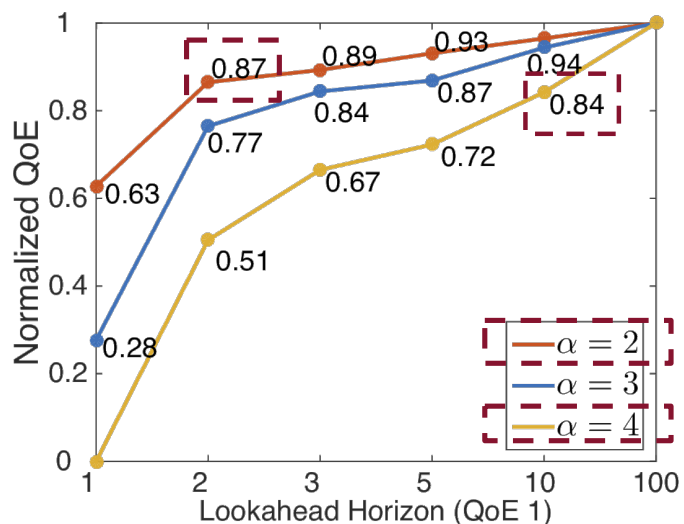


Algorithm 2 Sliding Horizon- m Streaming

Input: S_1 : initial state; α and β : startup parameters; m : look-ahead horizon; N : live streaming duration; $\{w_i, rtt_i, i \in [1, N]\}$: available bandwidth and rtt; \mathcal{R} : available rates.

Output: $\{r_i, i \in [1, N]\}$: rate sequence for all segments

- 1: Download the first β segments using predefined rate selection strategy $r_{[1, \dots, \beta]}$, obtain $S_{\beta+1}$
- 2: **for** each segment $i \in [\beta + 1, N]$ **do**
- 3: $rr_i^{(m)} = \text{Horizon-}m(S_i, m, \{w_{[i, i+m-1]}, rtt_{[i, i+m-1]}\}, \mathcal{R})$
- 4: $r_i = rr_i^{(m)}[1]$
- 5: $S_{i+1} = f(S_i, r_i, \{w_i, rtt_i\})$
- 6: **end for**
- 7: **return** $r_{[1, \dots, N]}$



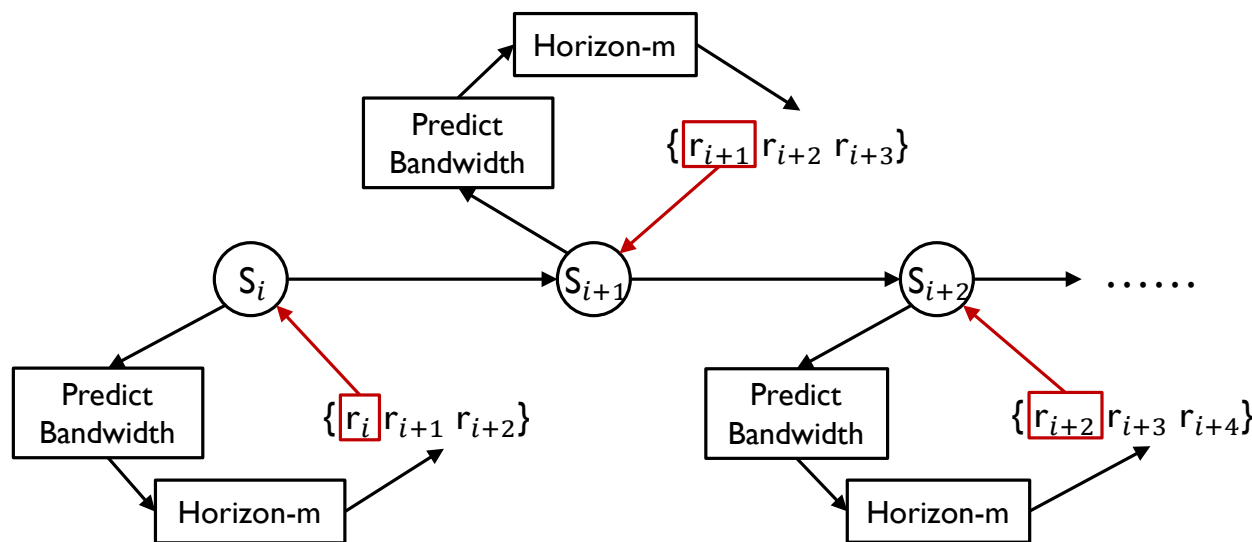
- When latency $\alpha=2$, small lookahead horizon ($m=2$) is needed to get high QoE.
- If $\alpha=4$, similar normalized QoE is achieved when $m=10$.

If latency is **short**, future information of **short** lookahead horizon is needed to achieve close-to-optimal QoE.



Model Predictive Control (MPC) for Live Streaming

- Future network information is NOT available.
- Bandwidth predictions
 - Harmonic Mean, Hidden Markov Model (HMM), Recursive Least Squared (RLS) and LSTM.

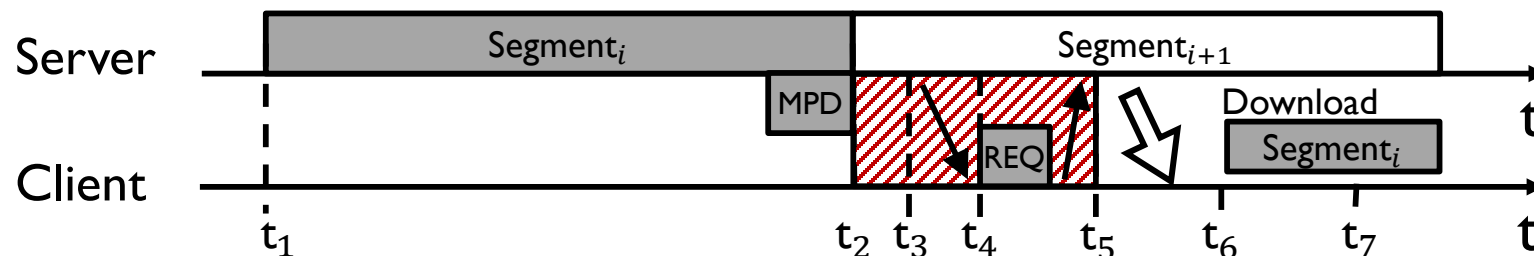


MPC based Practical Live Streaming Algorithm

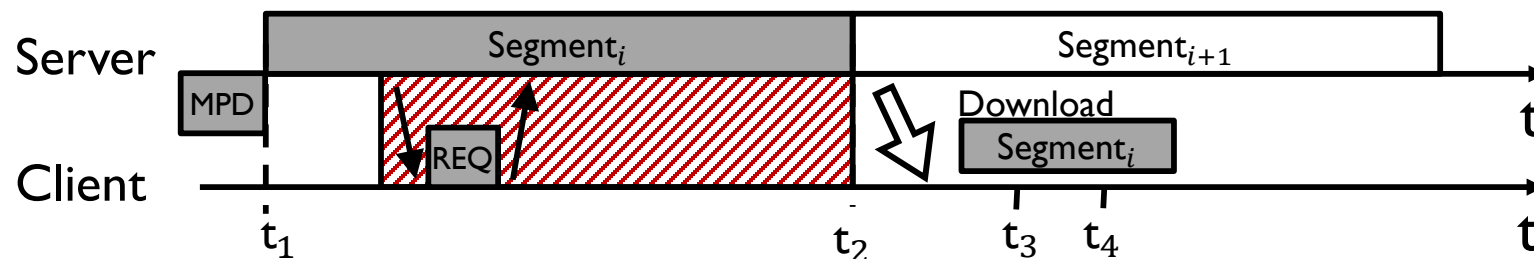


Segment & Chunk based Streaming

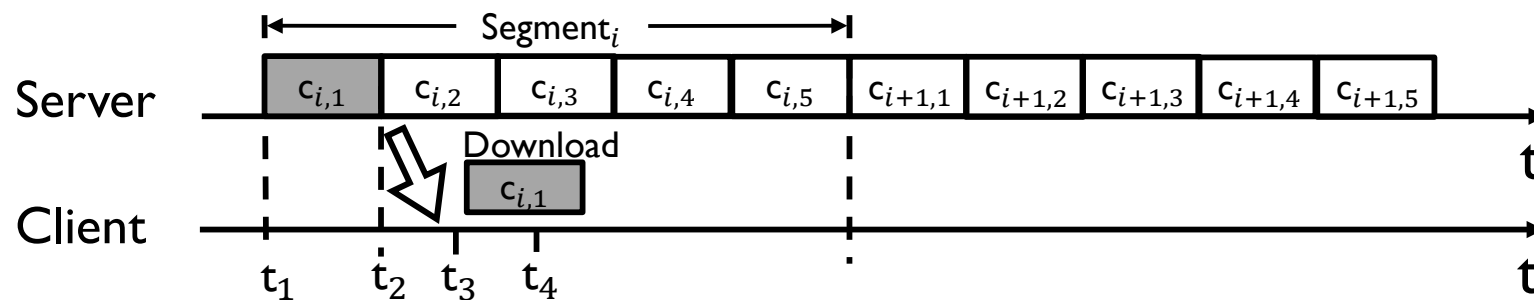
- Segment Mode



- Server-wait Mode

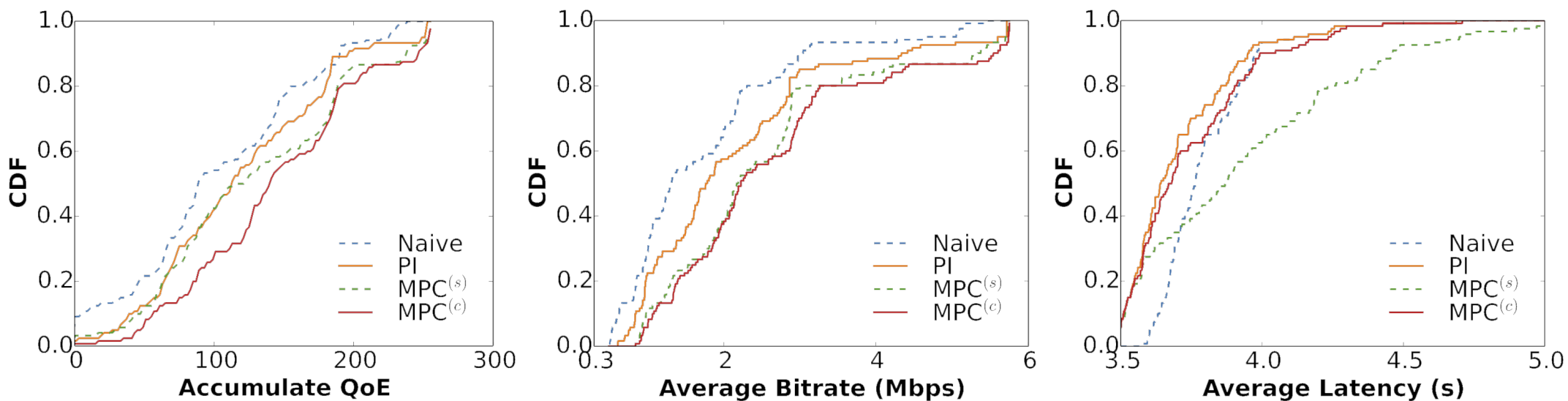


- Chunk Mode



Trace-driven Experiments and Evaluation

- 4G cellular bandwidth dataset with 150 traces collected in NYC.
- Naïve ($\gamma \hat{\omega}$), PI-Controller ($\gamma_p \hat{\omega}$) and MPC (segment and chunk mode).



- MPC based algorithms outperform Naive and PI-Controller.
- MPC^s suffers more latency (caused by freeze) than MPC^c.
- MPC^c achieves highest QoE with highest bitrate and lowest latency in most cases.



Conclusions & Ongoing Work

- Low latency is crucial, balance between latency and other QoE metrics
- MPC based streaming algorithms can improve the QoE performance with low latency.
- Chunk-based delivery is helpful to support low latency live video streaming.

- Optimal Streaming Policy from Deep Reinforcement Learning (DRL) vs. Model-based RL
- Optimal Playback Pace Adaption



THANK YOU!