中国科学院计算技术研究所
INSTITUTE OF COMPUTING TECHNOLOGY, CHINESE ACADEMY OF SCIENCES

Lumos: towards Better Video Streaming QoE through Accurate Throughput Prediction

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Adaptive Bitrate (ABR) Streaming

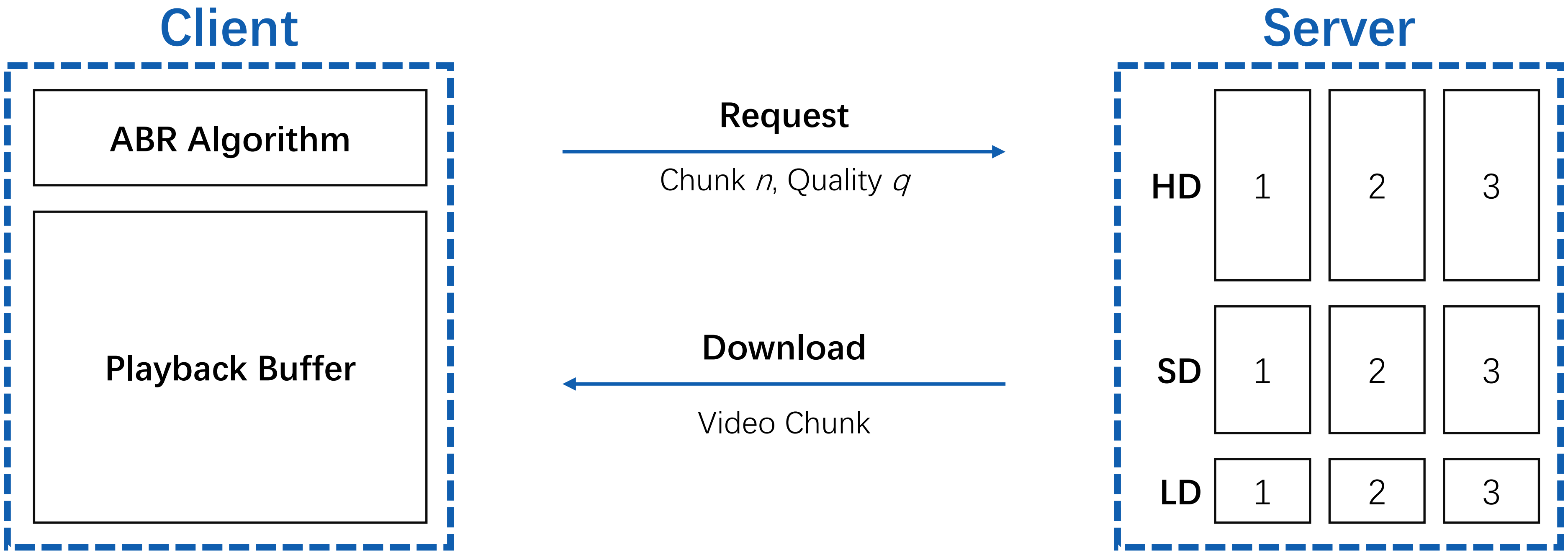
- HTTP-based video streaming dominates the Internet traffic nowadays, standardized as **DASH** (Dynamic Adaptive Streaming over HTTP)
- In DASH, the player runs **ABR** (Adaptive Bitrate) algorithm to select bitrate for each chunk, in order to optimize **QoE** (quality of experience)

$$QoE = \sum_{k=1}^{N} \boldsymbol{q(R_k)} - \mu \sum_{k=1}^{N} \mathbf{max}\left(\left(\frac{\boldsymbol{d_k(R_k)}}{\boldsymbol{T_k}} - \boldsymbol{B_k}\right), \mathbf{0}\right) - \lambda \sum_{k=1}^{N-1} \left|\boldsymbol{q(R_{k+1})} - \boldsymbol{q(R_k)}\right|$$

Quality	Rebuffering Time	Quality Switch

Adaptive Bitrate (ABR) Streaming

- DASH player runs **ABR** algorithm to optimize **QoE**
  - Goal: Higher quality; Lower rebuffering time; Fewer quality switches
  - Input: Application throughput, buffer occupancy, etc.
  - Output: Quality *q* (usually represented as bitrate level *r*) of chunk n



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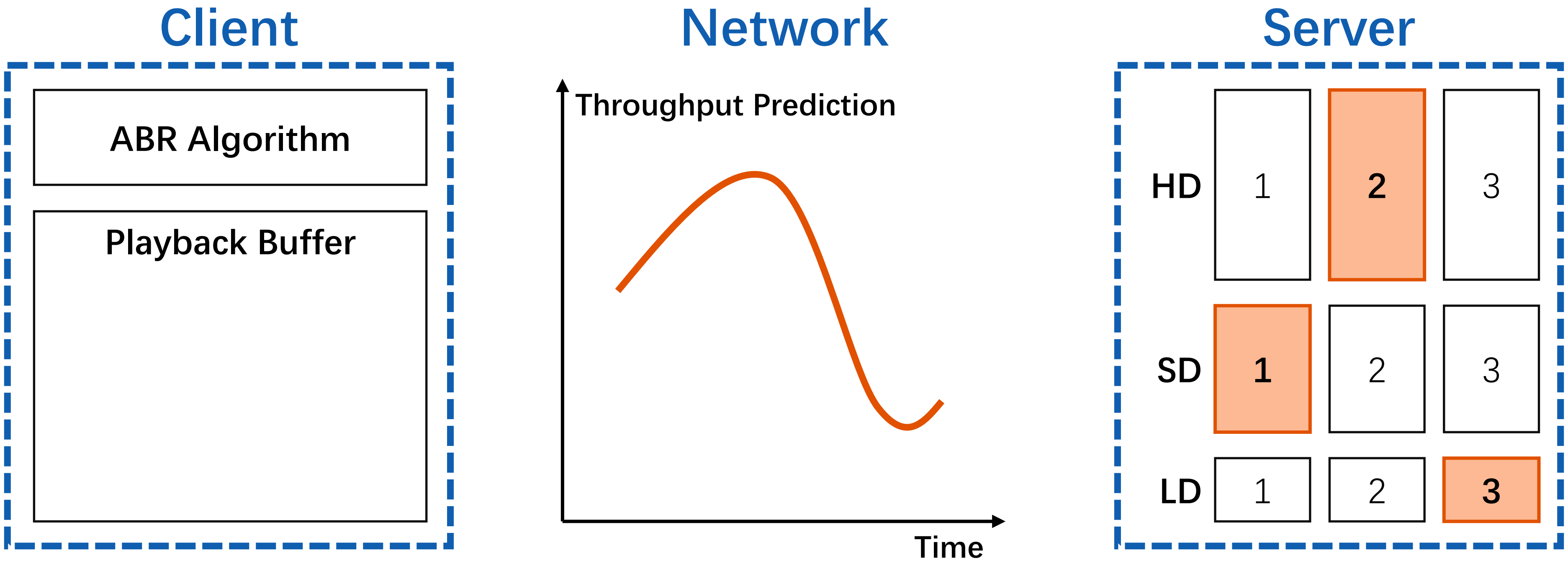

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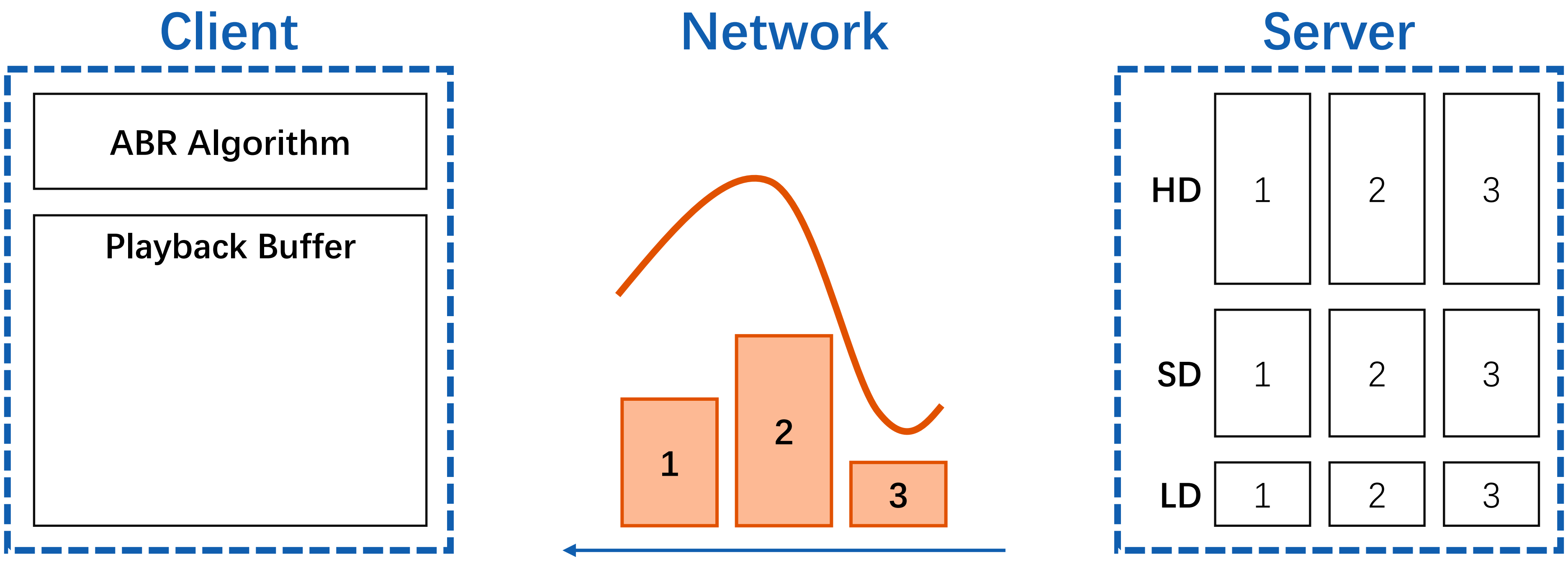

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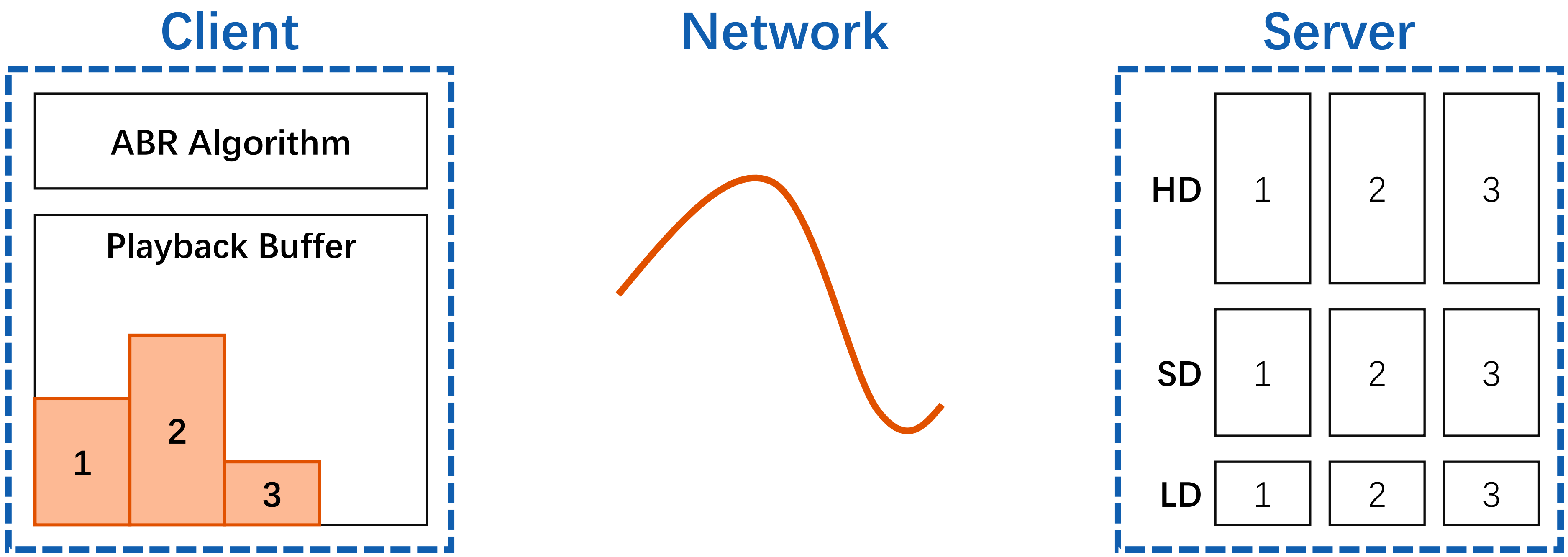


Throughput Prediction in ABR

❖ ABR algorithms can be classified into four categories

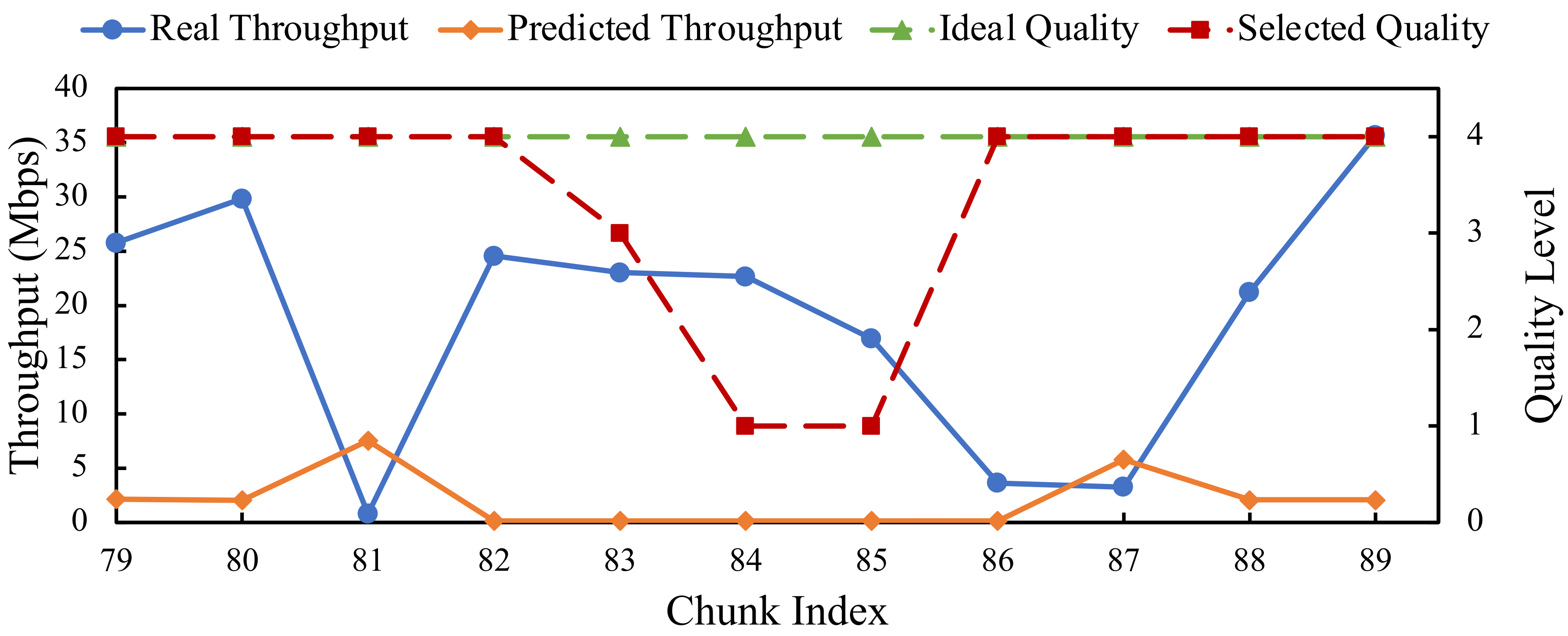
1 Rate-based	2 Buffer-based	3 Mixed	4 Learning-based
FESTIVE (CoNEXT'12) CS2P (SIGCOMM'16)	BBA (SIGCOMM'14) BOLA (INFOCOM'16)	MPC (SIGCOMM'15) PIA (INFOCOM'17) Fugu (NSDI'20)	Pensieve (SIGCOMM'17) Comyco (MM'19) Stick (INFOCOM'20)

- ①③: originally **require throughput prediction**
- ②④: **tend to rely on throughput prediction** when deployed in real-world environments
  - BOLA (INFOCOM'16) → DYNAMIC (MMSys'18)
  - Pensieve (SIGCOMM'17) → ABRL (ICML RL4RealLife'19)

Accurate throughput prediction is vital to improve QoE of ABR algorithms

Harm of Inaccurate Prediction

- Inaccurate throughput prediction decreases QoE
  - A real case of **RobustMPC** (SIGCOMM'15)
  - Predicted Throughput = Harmonic Mean of past samples / (1 + max error rate)



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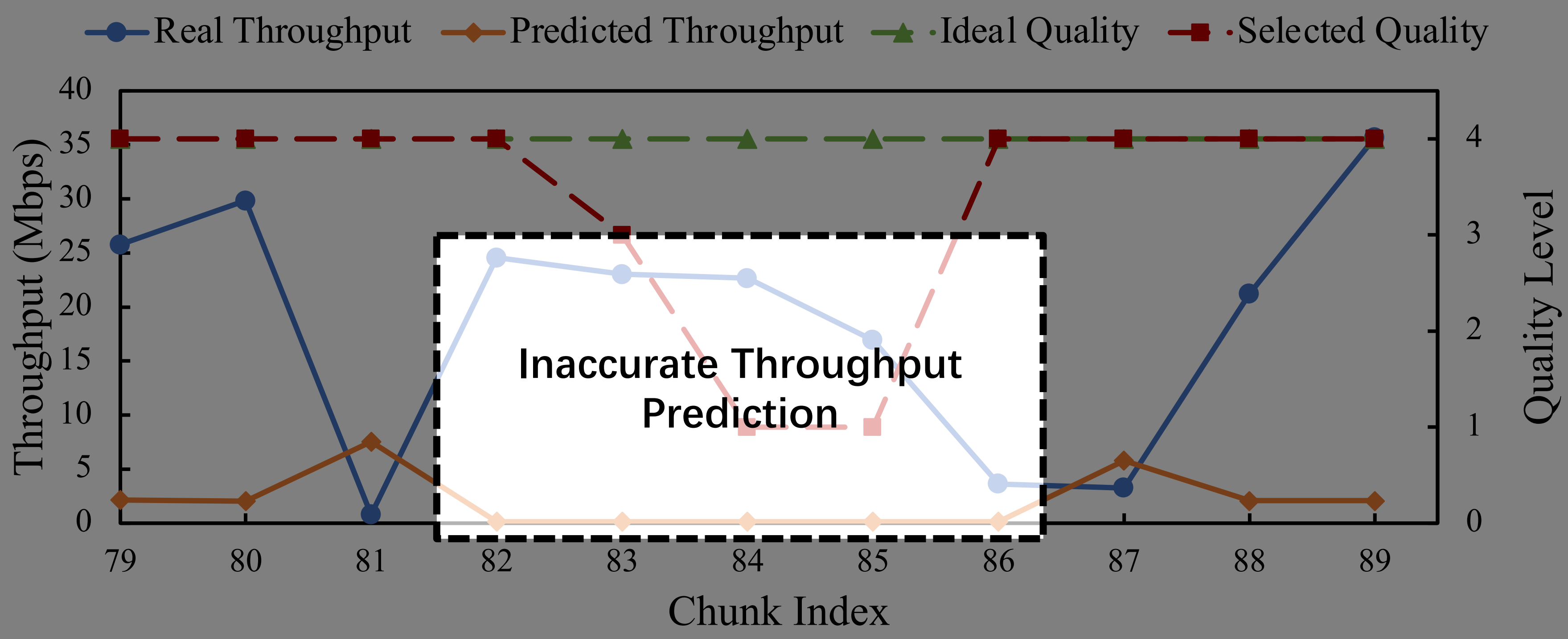

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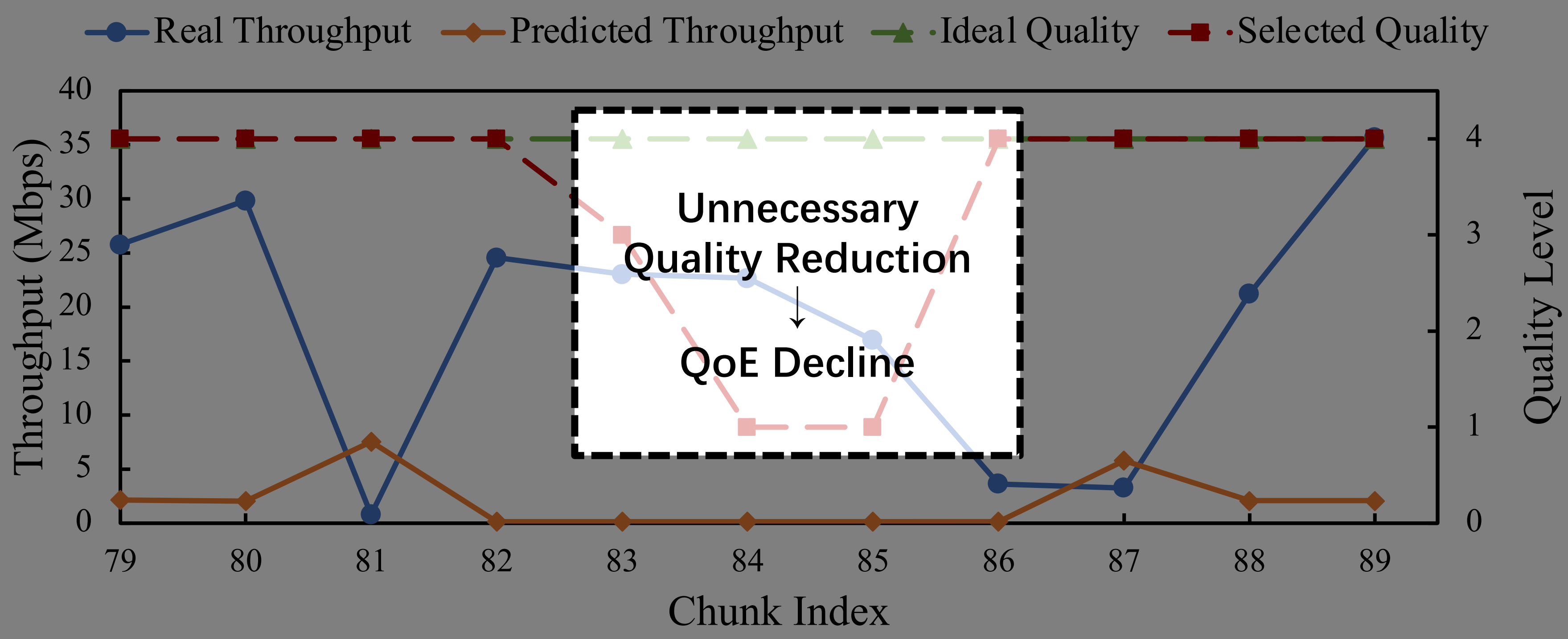
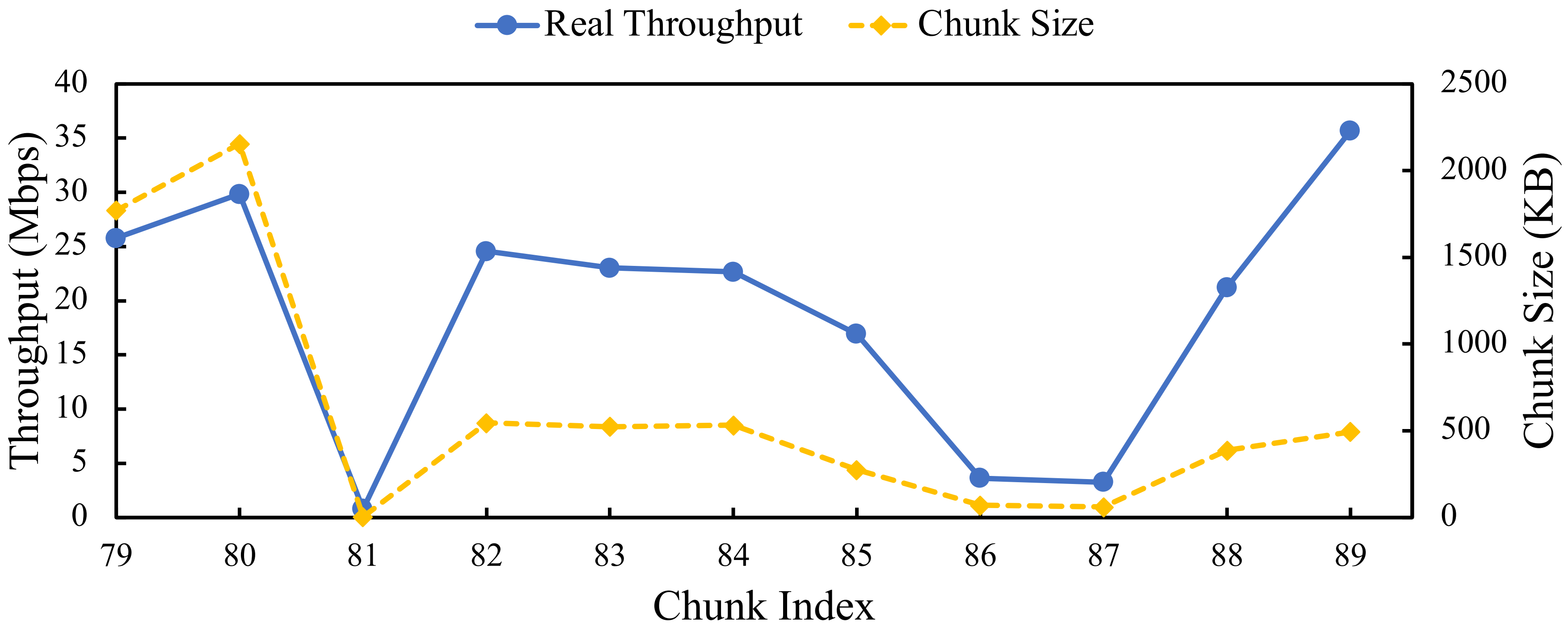


Dose Throughput Mean Network Conditions?

❖ Throughput Fluctuation

- Previous works attribute throughput fluctuation only to the change of **network conditions**
- However, it seems that **throughput changes in the same trend as chunk size does**



Chunk throughput may be not only determined by network conditions

Our Goal

Fundamental Problem in ABR streaming:

How to achieve accurate throughput prediction to assist ABR algorithms to optimize QoE?

Key Problems

- A predictor contains 3 components

$$Prediction = f(Features)$$

1

Input Features

What **factors** assist to achieve better prediction?

2

Output Target

Which one of **throughput** and **delivery time** is a better target to predict?

3

Mapping Function

Which **model** is more suitable for prediction?

Solution

- Correspondingly, our solution includes 3 steps

1	2	3
Identify Features	**Select Target & Model**	**Implement Predictor**
Qualitative Analysis Quantitative Verification	Controlled Experiment	Design Principle Real-world Deployment

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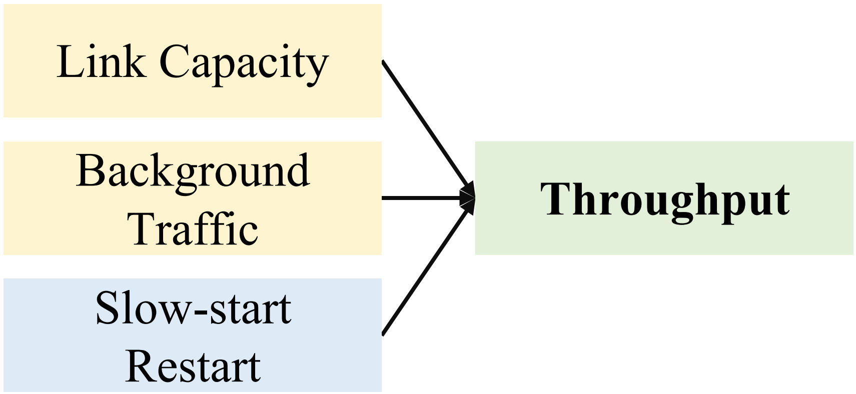
Identify Features

❖ Academic research evolves in this area

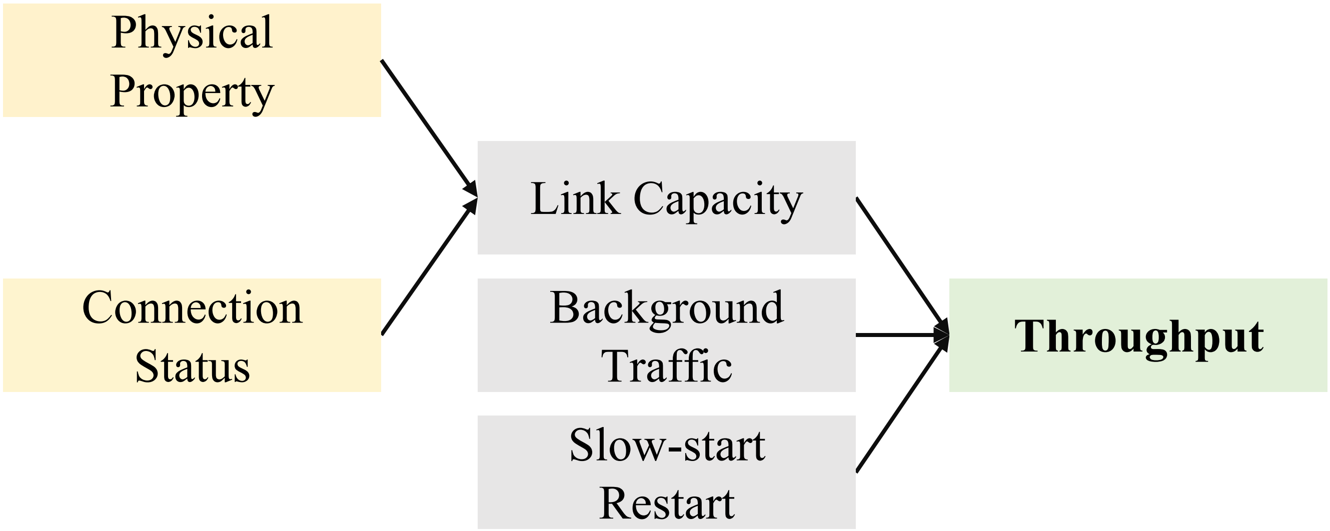


2012

Background traffic makes it hard to predict chunk throughput

Identify Features

❖ Academic research evolves in this area

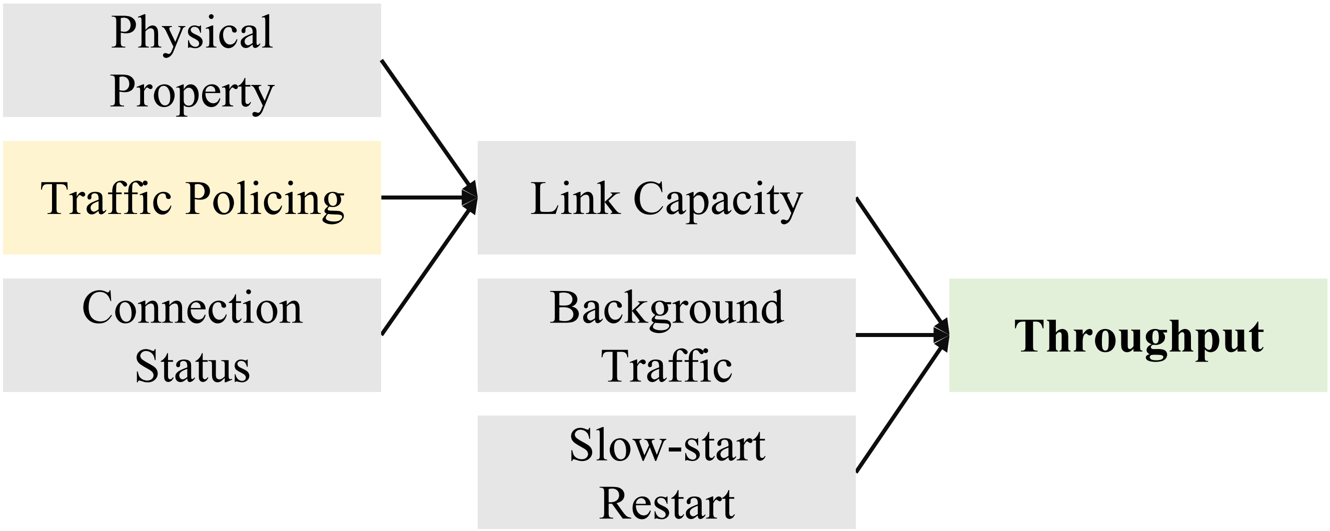


2016

Connections with similar status
exhibit similar throughput patterns

Identify Features

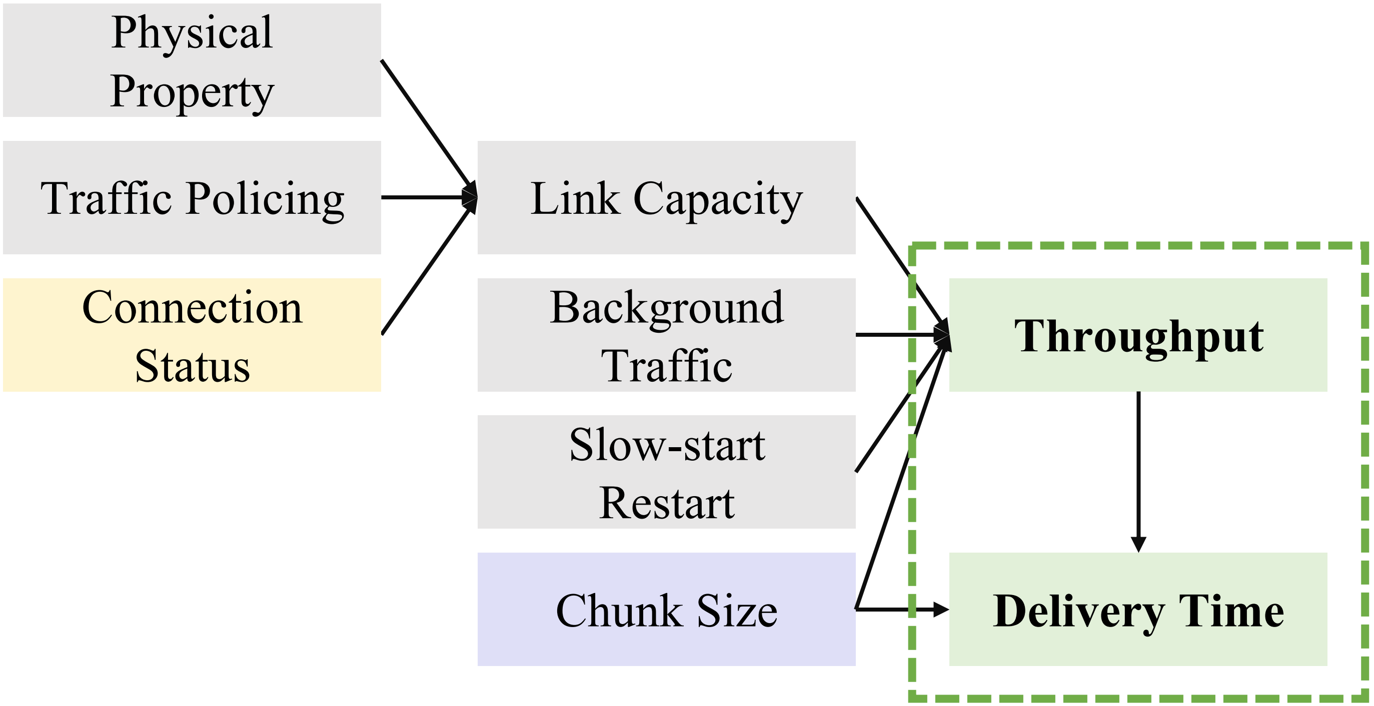
❖ Academic research evolves in this area



2016 | **Traffic Policing** impacts video throughput

Identify Features

❖ Academic research evolves in this area

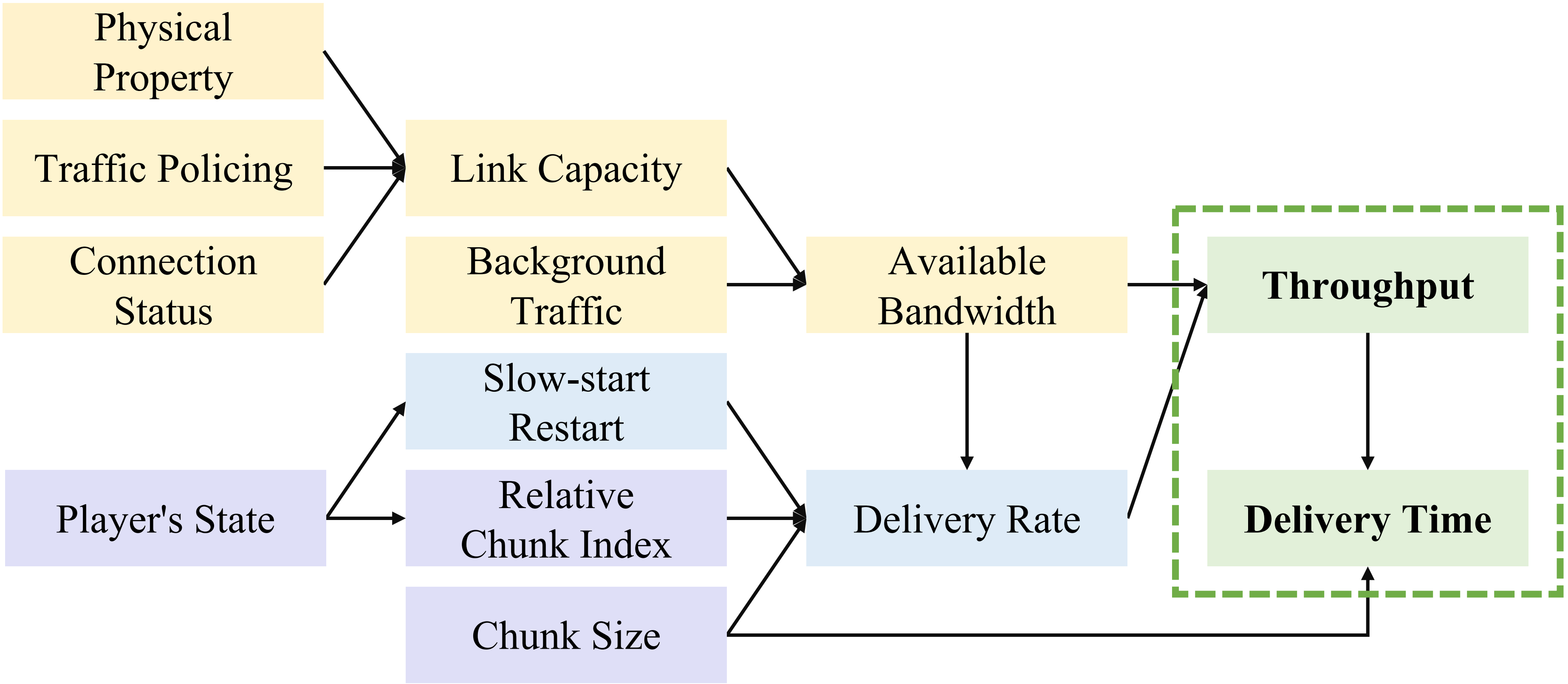


2020

Chunk size is useful to predict **delivery time**

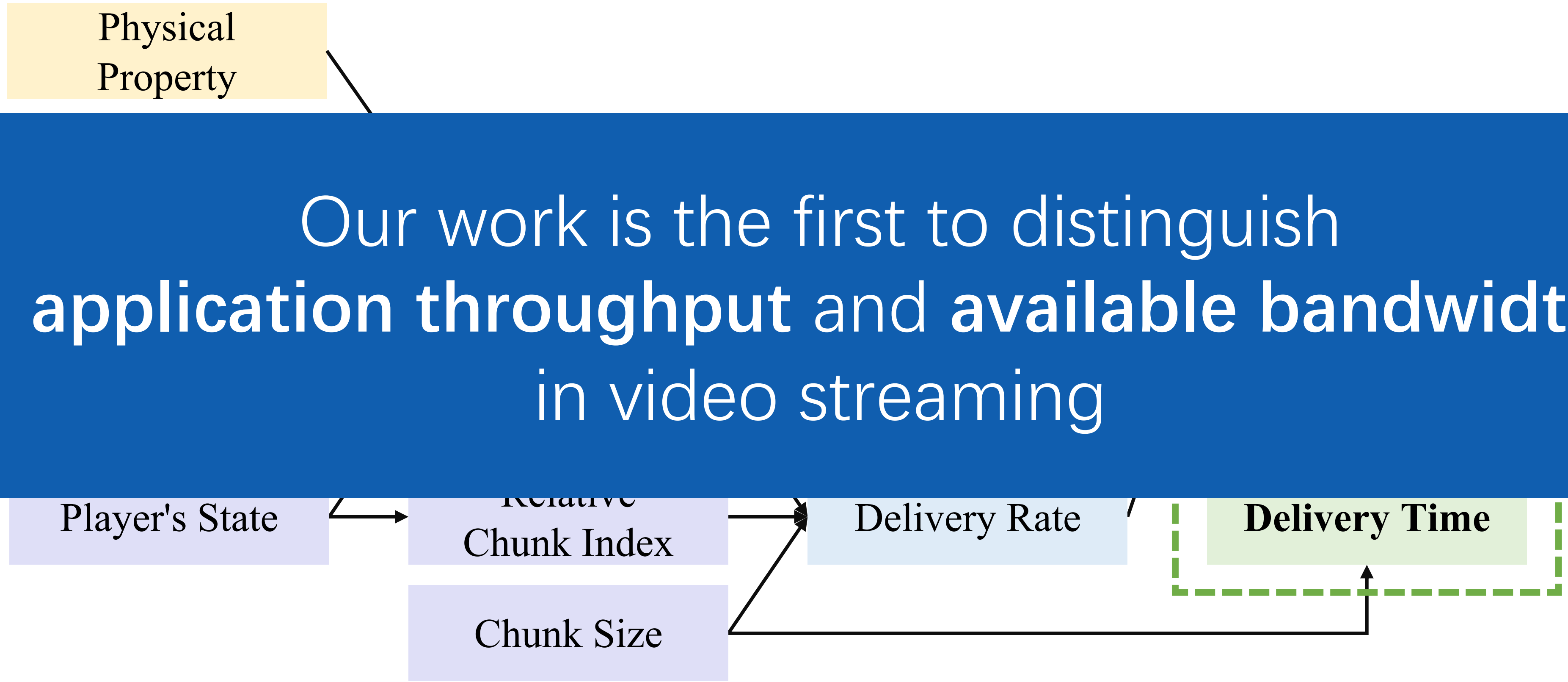
Identify Features

❖ **Theoretical Framework**: all factors impacting throughput and delivery time



Identify Features

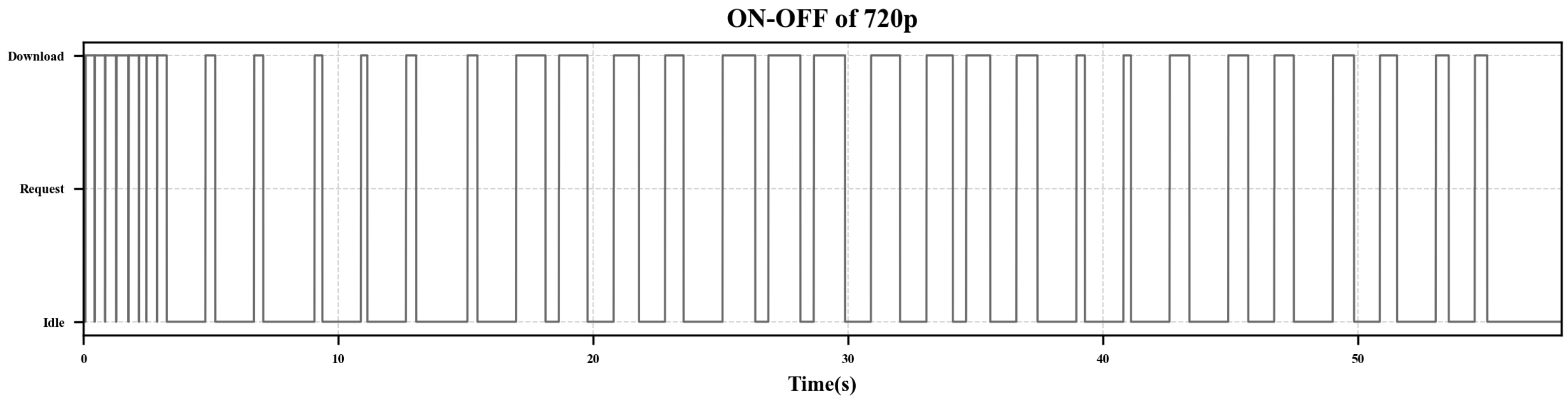
❖ **Theoretical Framework**: all factors impacting throughput and delivery time



Our work is the first to distinguish **application throughput** and **available bandwidth** in video streaming

ON-OFF Period in Video Streaming

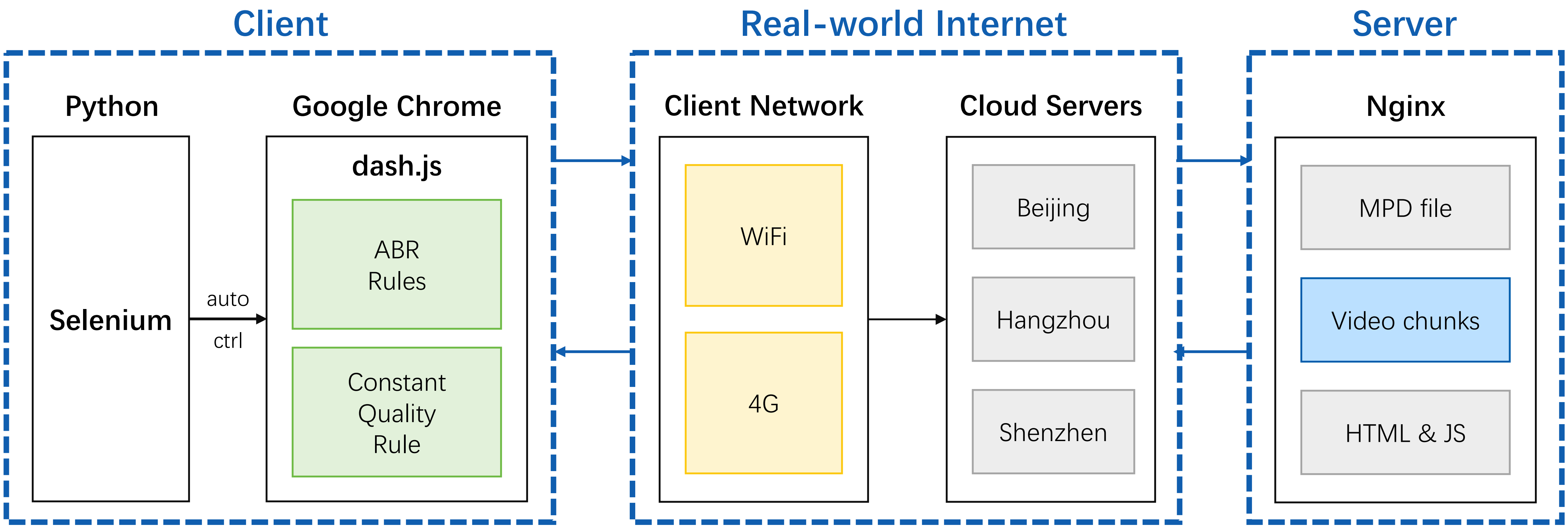
- ON-OFF: A unique behavior of video streaming
  - Player requests for chunks **periodically** rather than **continuously** after the start-up phase
- Slow-start Restart
  - If OFF period exceeds a timeout (200ms in Linux), the server will reset *cwnd* to its initial size, and return to slow-start phase for the next transmission
- Player's State
  - **Buffering State**: *cwnd* is adjusted continuously in subsequent chunks
  - **Steady State**: slow-start restart occurs when delivering each chunk



Collect Dataset

❖ Automated video streaming measurement platform

- **Video**: Elephant Dream & Big Buck Bunny at [300, 750, 1200, 1850, 2850, 4300] Kbps
- **Client**: based on Selenium to automictically control Chrome browser to run dash.js player
- **Server**: deployed on cloud servers in 3 cities, hosting video contents and HTML & JS codes



Collect Dataset

❖ Automated video streaming measurement platform

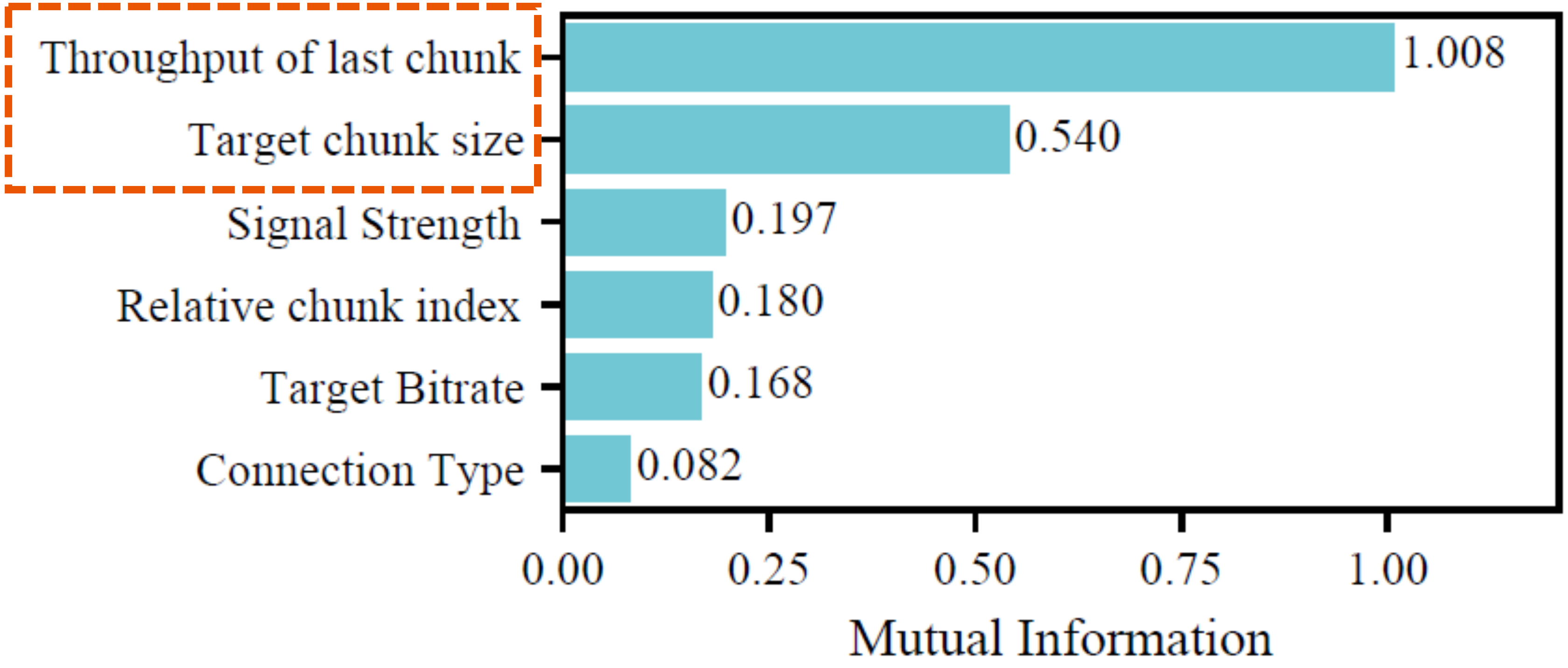
- Collected information

Client Player	Server Transport Layer
Constant bitrate rule & ABR rules	tcp_probe
Playback Information chunk size, delivery time, application throughput, buffer level, inactivity time, rebuffering time, etc. **Signal Strength** WiFi RSSI, 4G RSRP & SINR	**TCP Information** *cwnd* size, *ssthresh*, smoothed RTT, inflight size, etc.

We collected data of **2500+ video sessions**, containing **300,000+ video chunks** from 2019.12.30 to 2021.05.18

Identify Features

❖ **Observation 1**: Throughput of last chunk and target chunk size are the two most important factors in throughput prediction

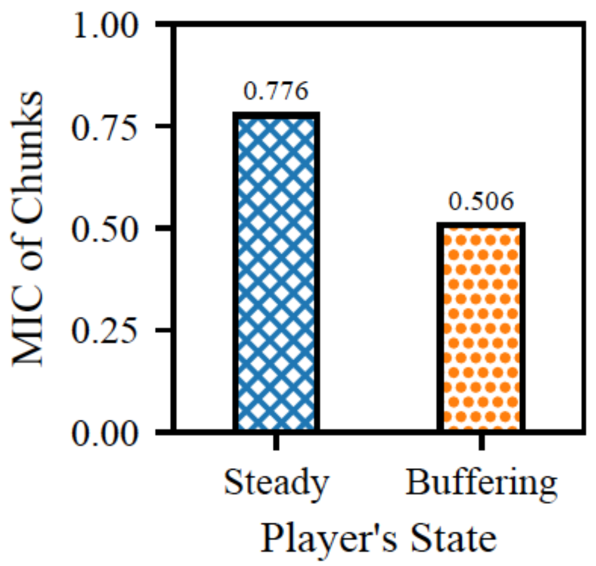


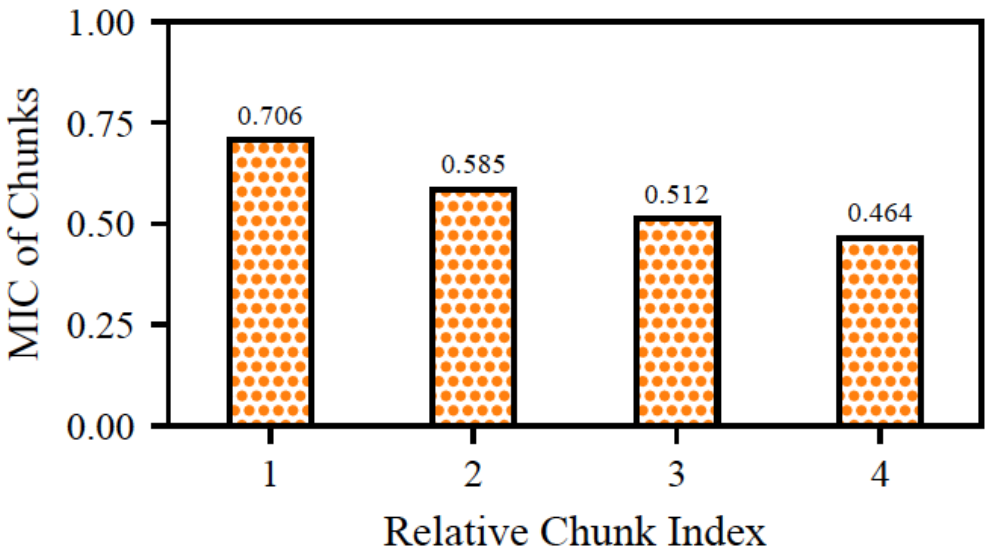
How does video chunk size affect application throughput?

Identify Features

❖ **Observation 2:** Correlation between throughput and chunk size is deeply affected by player's state, relative chunk index, and signal strength of the client

- 1. Player's state
  - The correlation in the Steady-State is higher than that in the Buffering-State
  - The correlation decreases as relative chunk index increases

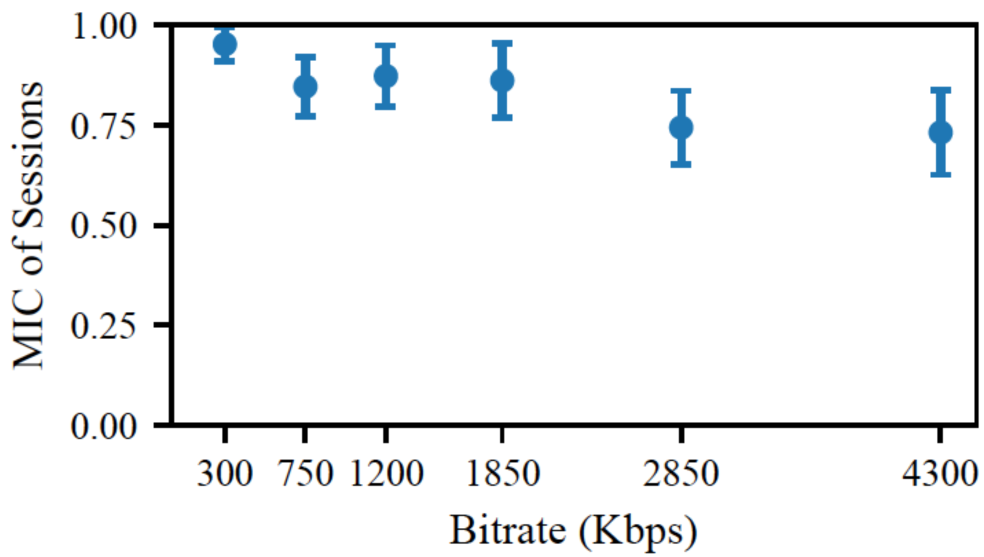




Identify Features

❖ **Observation 2:** Correlation between throughput and chunk size is deeply affected by <u>player's state</u>, <u>relative chunk index</u>, and <u>signal strength of the client</u>

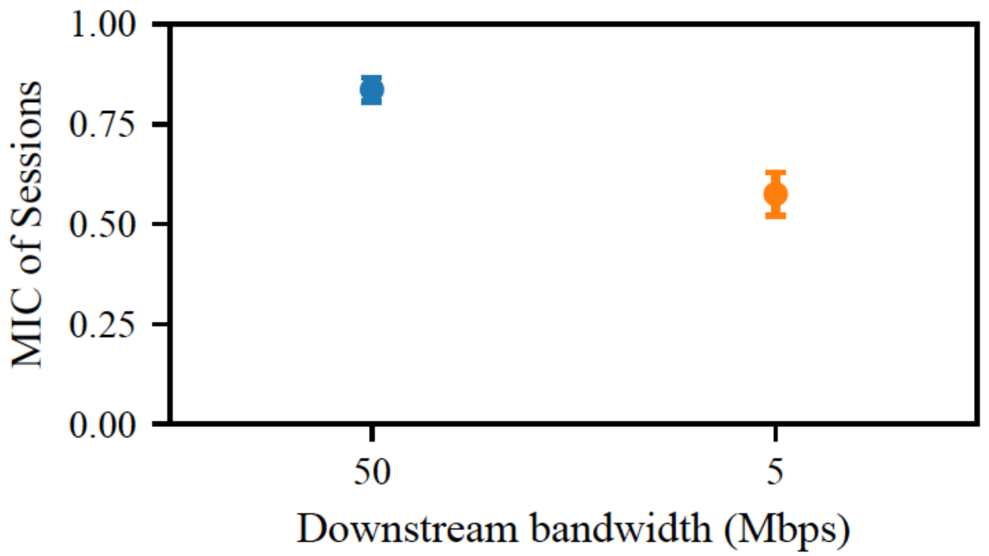
- 2. Bitrate level
  - The correlation becomes lower as the bitrate increases

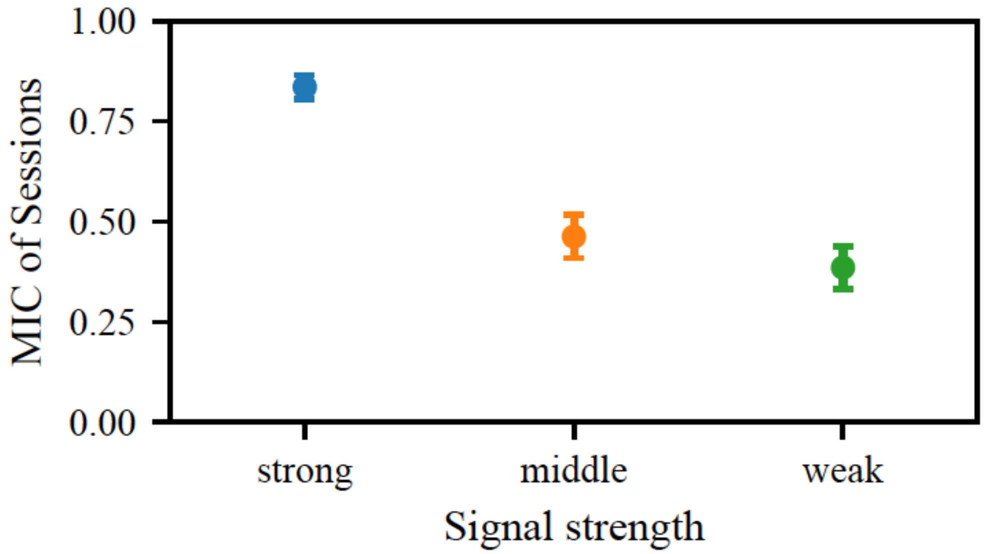


Identify Features

❖ **Observation 2:** Correlation between throughput and chunk size is deeply affected by player's state, relative chunk index, and signal strength of the client

- 3. Network condition
  - Downstream bandwidth of the server
  - Wireless signal strength of the client





Application throughput is determined by both **available bandwidth** and **delivery rate**

Identify Features

❖ Features of Predictor

1

Player's State

relative index of the last chunk

2

Chunk Information

bitrate & size of the last chunk
bitrate & size of the target chunk

3

Network conditions

max throughput of past chunks
max delivery time of past chunks
connection type
throughput of the last chunk

Solution

❖ Correspondingly, our solution includes 3 steps

1	2	3
Identify Features	**Select Target & Model**	Implement Predictor
Qualitative Analysis Quantitative Verification	Controlled Experiment	Design Principle Real-world Deployment

Select Target & Model

- Output Target: Throughput and Delivery Time can be converted to each other with chunk size given
  - **Throughput**: corresponding to bitrate (output of ABR algorithms)
  - **Delivery Time**: used to calculate QoE (target of ABR algorithms)

- Mapping Function: Data-driven methods
  - Multiple Linear Regression (MLR)
  - Decision Trees
  - Deep Neural Networks (DNN)
    - Effective, however heavyweight and short of interpretability, and thus hard to deploy[1][2]

[1] Z. Meng, J. Chen, Y. Guo, C. Sun, H. Hu, and M. Xu, "Pitree: Practical implementation of abr algorithms using decision trees", MM, 2019
[2] Z. Meng, M. Wang, J. Bai, M. Xu, H. Mao, and H. Hu, "Interpreting deep learning-based networking systems", SIGCOMM, 2020

Select Target & Model

- Controlled Experiment
  - **Target:** Throughput Predictor vs. Delivery Time Predictor
  - **Model:** Decision Tree Predictor vs. MLR Predictor

	Throughput	Delivery Time
Decision Tree	Tree-Thput	Tree-DTime
MLR	MLR-Thput	MLR-DTime

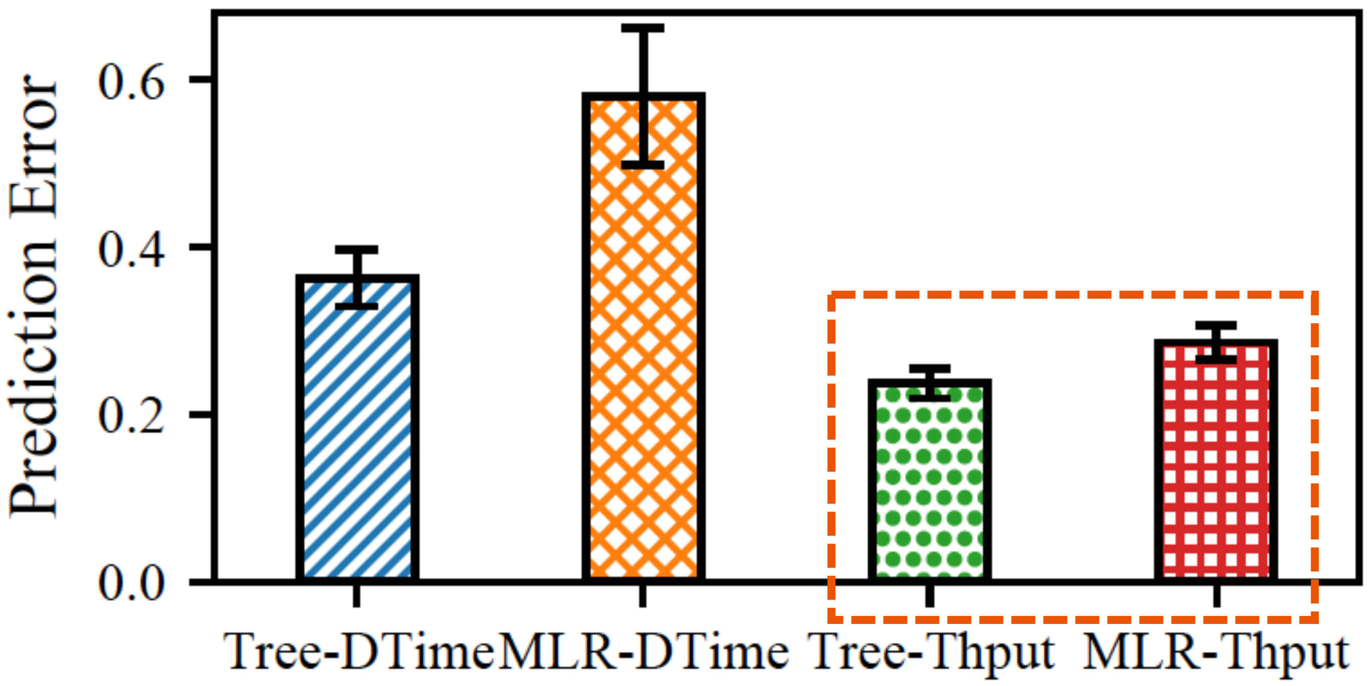
- Metric: Absolute Normalized Prediction Error

$$Err(DTime) = \frac{1}{N}\sum_{k=1}^{N}\frac{\widehat{DT_k} - DT_k}{DT_k}$$

* The predicted throughput is converted to delivery time for comparison with the directly predicted delivery time

Select Target & Model

- **Observation 3**: <u>Throughput prediction achieves better accuracy</u> than delivery time prediction does

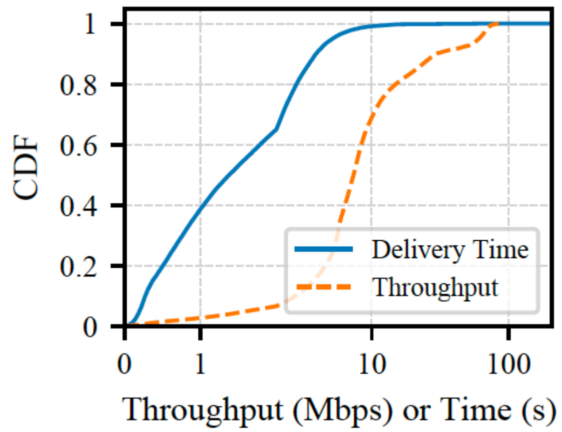


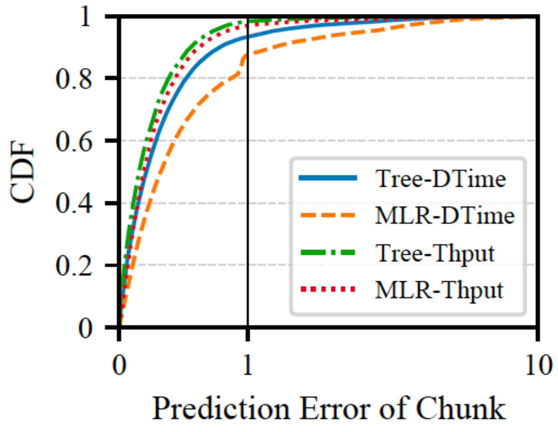
* The predicted throughput is converted to delivery time for comparison with the directly predicted delivery time

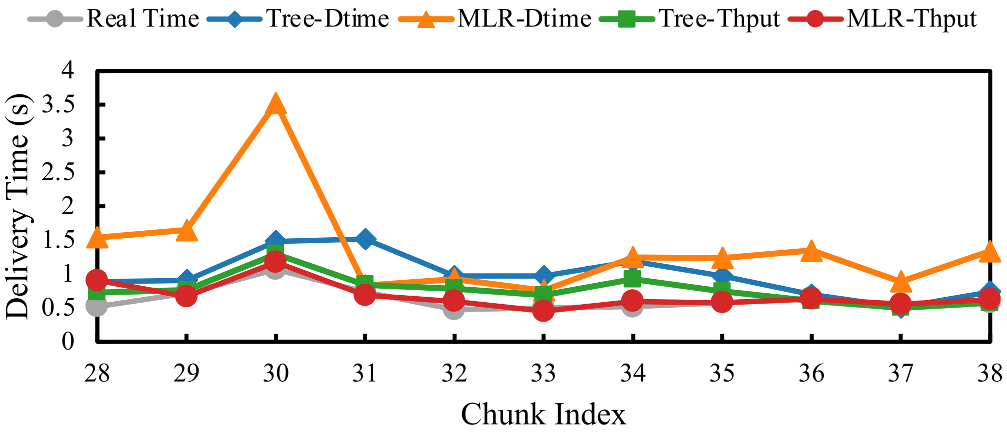
Select Target & Model

❖ **Observation 3**: Throughput prediction achieves better accuracy than delivery time prediction does

- The **long-tailed distribution** of delivery time causes data-driven predictors tend to overestimate the real values
  - 0.8% of chunks lie in the 95% tail of time interval (from 10s to 208s)
- Delivery time predictors perceive prediction error of over 100% for more chunks (6.6%~12.4%) than throughput predictors (1.7%~3.0%)







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Key Problems

- A predictor builds a map between input and output, containing 3 components

$$Prediction = f(Features)$$

1 **Input Features**

What **factors** assist to achieve better prediction?

2 **Output Target**

Which one of **throughput** and **delivery time** is a better target to predict?

3 **Mapping Function**

Which **model** is more suitable for prediction?

Implement Predictor

❖ Design Principle

1	2	3
Input Features	**Output Target**	**Mapping Function**
What **factors** assist to achieve better prediction?	Which one of **throughput** and **delivery time** is a better target to predict?	Which **model** is more suitable for prediction?
Player's State **Chunk Information** **Network Conditions**	**Throughput**	**Decision Trees**

Lumos: decision-tree-based throughput predictor for ABR streaming

Lumos Mechanism

❖ Train

- Method: Classification and Regression Tree (CART)
  - Regression tree
  - Loss function: mean squared error (MSE)
- Dataset: 700+ ABR video sessions in the real world, containing 69,000+ chunks
  - Training set accounts for 70%
  - Data of various combinations of network conditions is balanced
- Optimization:
  - Prepruning and cost complexity pruning
  - Exhaustive grid search
  - K-fold cross validation

❖ Deploy

- Parameters of Lumos models are dumped in JavaScript, loaded in dash.js player

Lumos with ABR algorithms

❖ Lumos as a plug-in of ABR algorithms

RB (CoNEXT'12)	**MPC** (SIGCOMM'15)	**BBA** (SIGCOMM'14)
replace HM predictor	**replace HM predictor**	**combine with prediction**
$R_k = \max_{1 \le j \le m} \{r_j, \frac{d_k(r_j)}{\hat{T}_{k\|r_j}} \le L\}$	$R_k = \arg \max_{r_j, 1 \le j \le m} \sum_{l=k}^{k+n-1} \widehat{QoE}\ (R_{l\|r_j})$	$R_k = \max_{1 \le j \le m} \{r_j, B_{lower} + \frac{d_k(r_j)}{\hat{T}_{k\|r_j}} - \frac{d_k(r_1)}{\hat{T}_{k\|r_1}} \le B_k\}$

Evaluation Setup

❖ Baselines

- Predictors
  - Lumos / MLR / HM / Robust-HM
- ABR algorithms
  - RB (CoNEXT'12) / MPC & RobustMPC (SIGCOMM'15) / BBA (SIGCOMM'14) / Pensieve (SIGCOMM'17)

❖ Environment: Real-world Internet

- On our video streaming measurement platform
- ~300 sessions under various network environments
  - Downstream bandwidth of the server: 50Mbps / 5Mbps
  - Connection types: WiFi / 4G
  - Signal strength: Strong / Middle / Weak

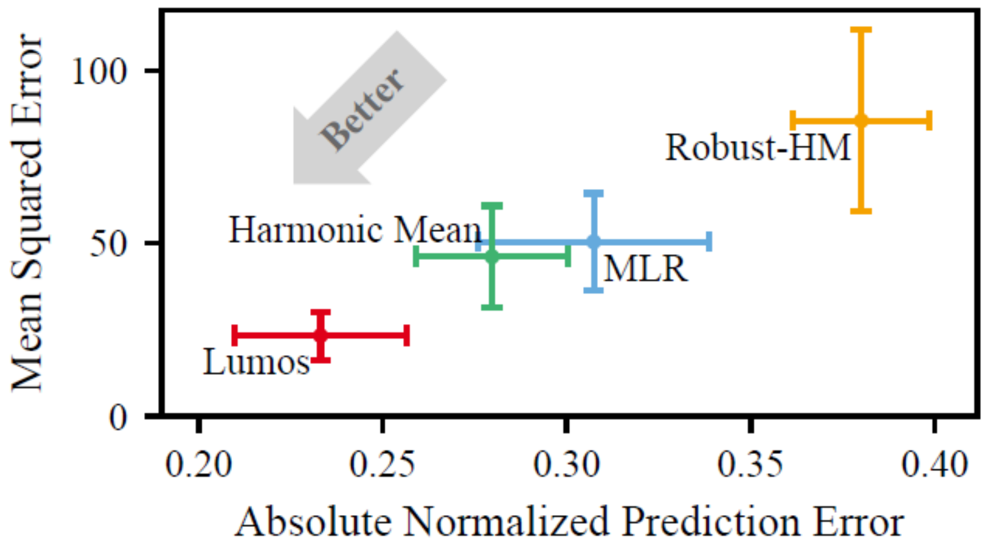
❖ Metrics

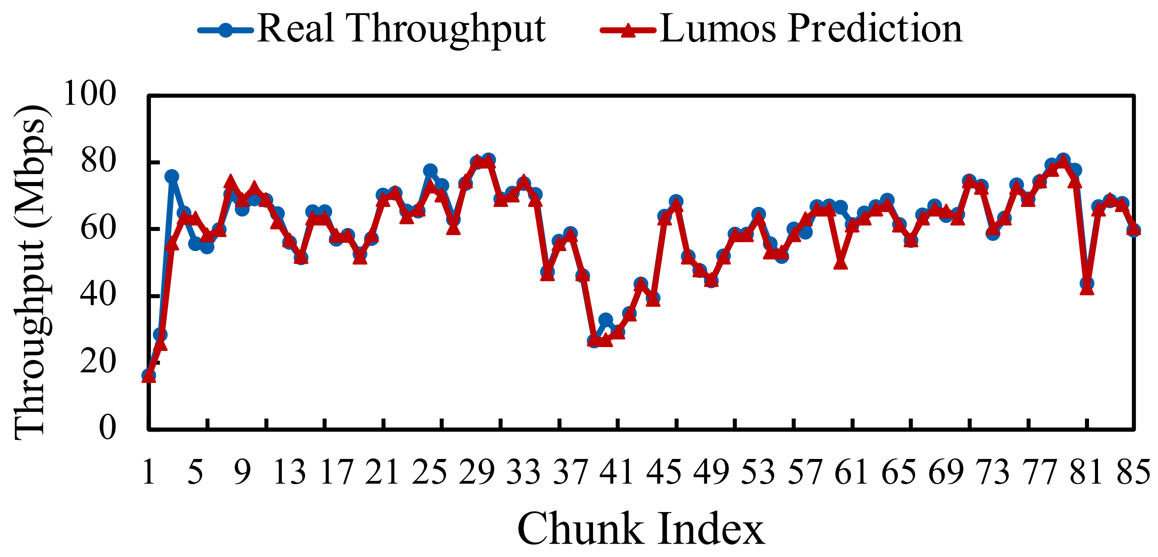
- Prediction accuracy of predictors
  - Prediction Error / Mean Squared Error (MSE)
- QoE performance of ABR algorithms
  - Higher quality / Lower rebuffering time / Fewer quality switches

Evaluation in real-world Internet

❖ Prediction Accuracy

- Lumos reduces prediction error by **16.8%~38.7%**, and MSE by **49.6%~72.8%**
- **Strong signal strength** of WiFi: prediction error is only **7.4%** in average
  - 57.7%~74% and 78.5%~90.5% improvement of the two metrics than others
- **Weak signal strength** where network is hard to predict: improve prediction accuracy over the two metrics by **9.1%~28.9%** and **17.8%~61.7%** respectively

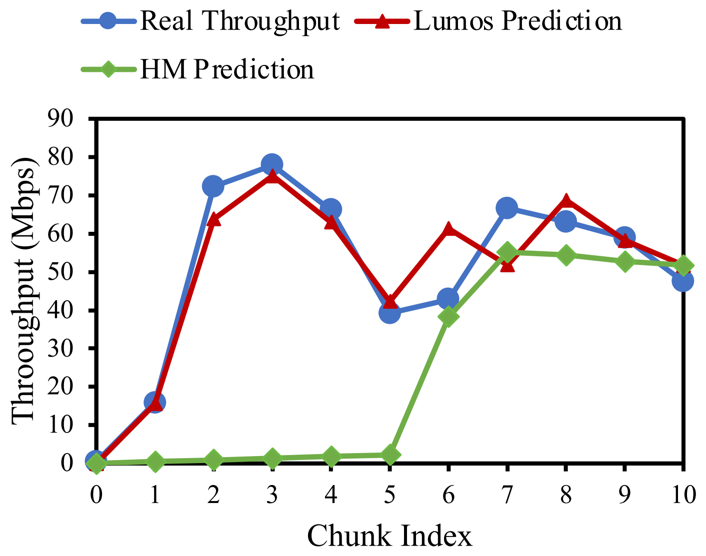


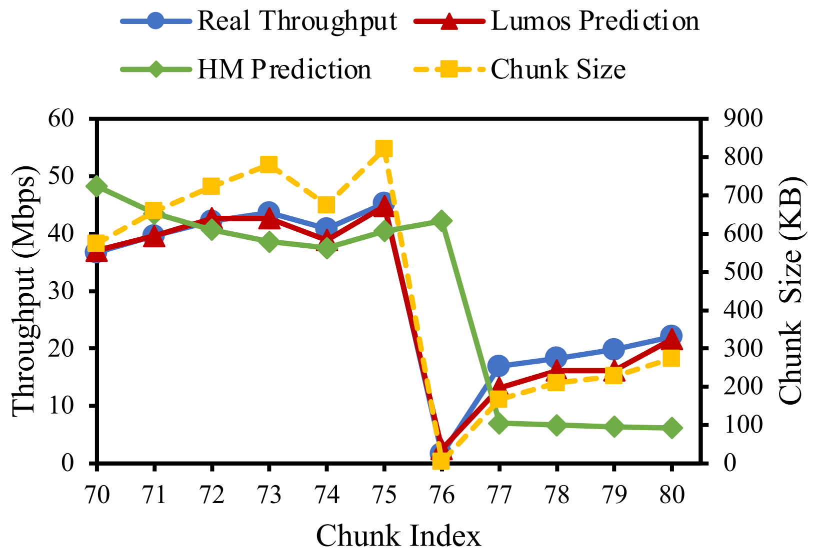


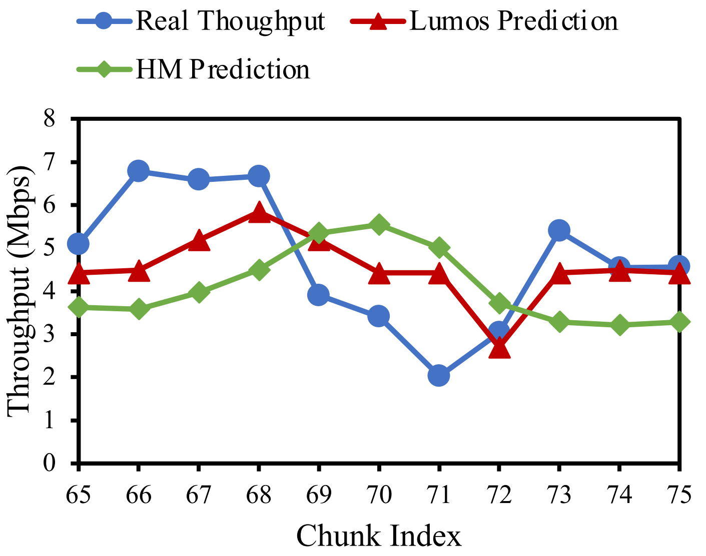
Evaluation in real-world Internet

❖ The Advantage of Lumos over HM (Harmonic Mean)

- Aware of network conditions and player's state: **start-up** phase
- Consider the fluctuation of chunk sizes: **strong** signal strength
- React quickly to bandwidth fluctuation: **weak** signal strength





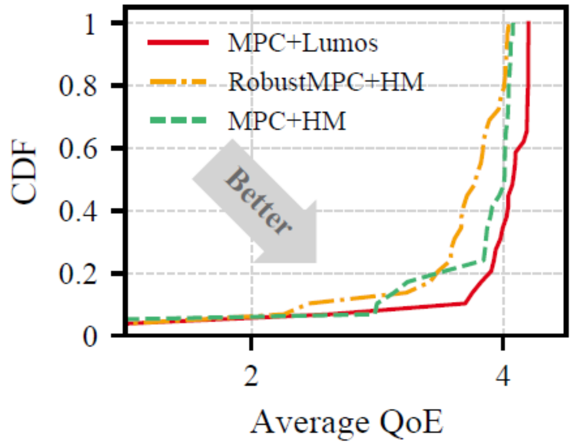


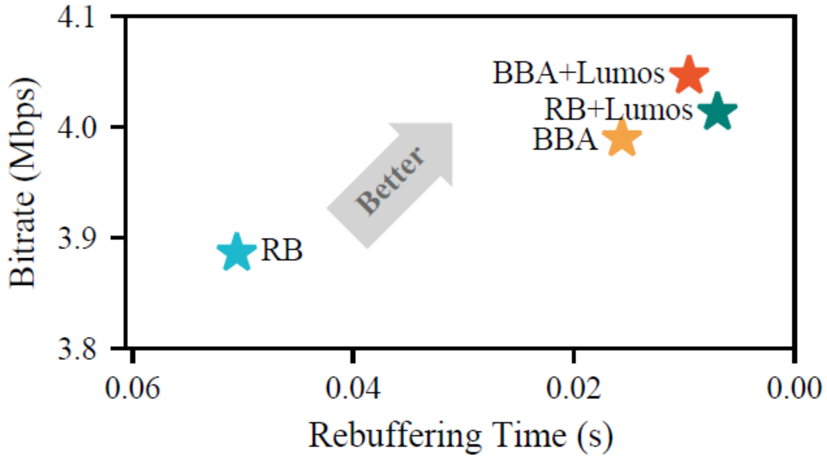
Lumos can distinguish the change of network conditions and application behavior

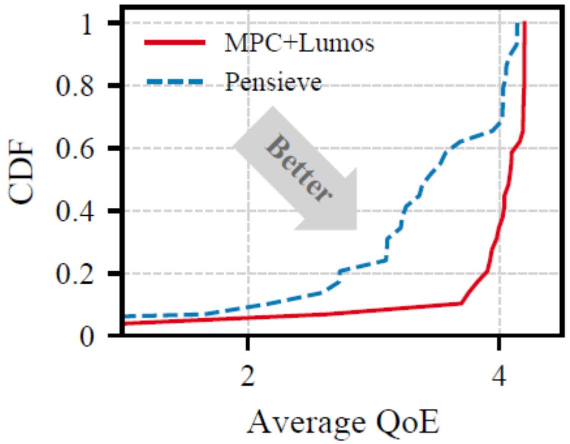
Evaluation in real-world Internet

❖ QoE of Lumos-assisted ABR Algorithms

- with **MPC**: improve QoE by **6.3%** over MPC and **8.7%** over RobustMPC
- with **RB** / **BBA**: reduce rebuffering time by **86.3%** and **37.5%**, and improve bitrate by **3.3%** and **1.3%**, compared with RB and BBA respectively
- vs. **Pensieve**: MPC+Lumos improves QoE by **19.2%** in average
  - Difference between Pensieve's simulator and the real world







Summary

❖ Contributions

- We construct a theoretical framework containing all the impacting factors in predicting throughput and delivery time for video streaming, and distinguish **application throughput** from **available bandwidth** for the first time.
- We build a **real-world** video streaming measurement platform, and collect dataset containing **2500+ sessions**. By data analysis and controlled experiments, we find that:
  - **Strong correlation exists between chunk size and throughput**. This correlation is deeply affected by player's state, relative chunk index, and signal strength of the client.
  - **Throughput is a better prediction target than delivery time** in terms of prediction error for data-driven predictors.
- We propose **Lumos**, a decision-tree-based accurate throughput predictor for ABR streaming. As a plug-in, Lumos assists ABR algorithms to achieve better QoE.

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Thanks!

Q&A

Presented by **Gerui Lv** from ICT, CAS