CS2P: Improving Video Bitrate Selection and Adaptation with Data-Driven Throughput Prediction

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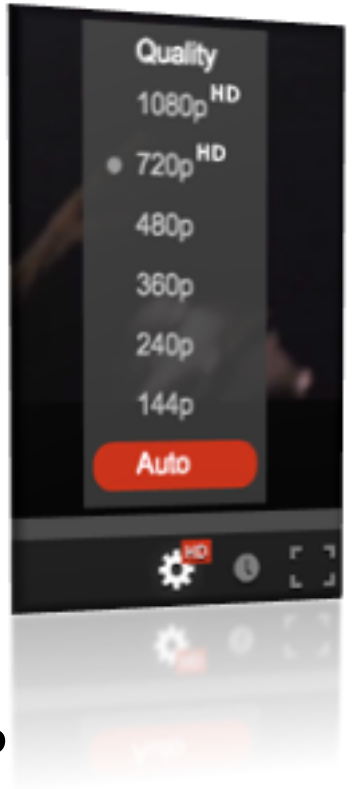
Bitrate adaptation is key for QoE



- DASH = Dynamic Adaptive Streaming over HTTP
- Entail new QoE metrics, e.g., low buffering, high video quality
- Need intelligent bitrate control and adaptation

Prior work: Accurate throughput prediction can help!

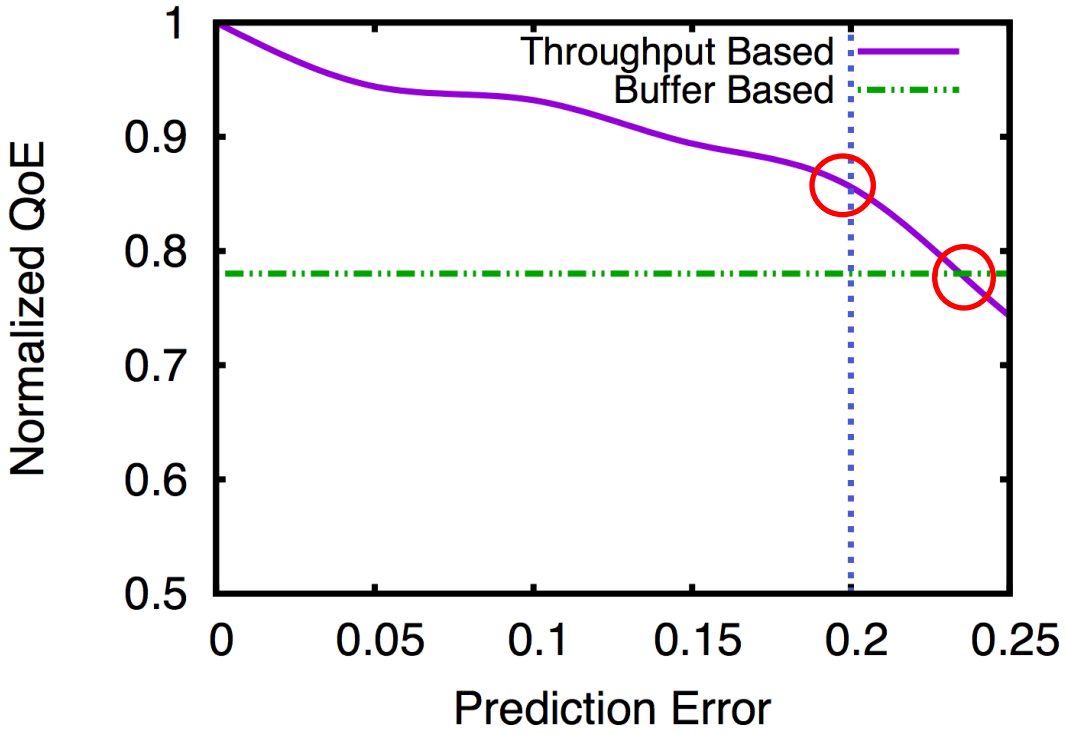
Accurate throughput prediction → Better initial bitrate selection

- Fixed bitrate

- Adaptive bitrate

Accurate throughput prediction → Better midstream adaptation

- Replicate the analysis by Yin et al. at SIGCOMM2015[1]
  - $Normalized\ QoE = \frac{Actual\ QoE}{Theoretical\ \text{optimal}}$



[1] X.Yin, et al. "A Control-Theoretic Approach for Dynamic Adaptive Video Streaming over HTTP". *ACM SIGCOMM, 2015*.
[2] T.Y. Huang, et al. "A Buffer-Based Approach to Rate Adaptation: Evidence from a Large Video Streaming Service". *ACM SIGCOMM, 2014*.

Open questions on predictability!

- Our understanding of throughput variability and predictability is quite limited.

- What types of prediction algorithms to use?
  - In the context of video bitrate adaptation
  - Prior approaches: 30%+ of predictions with error ≥0.2

Our work and contributions

A large-scale analysis, providing data-driven insights for predicting the throughput accurately.

Design of CS2P (Cross-Session Stateful Predictor): Improving bitrate selection and adaptation via throughput modeling.

A practical implementation of CS2P and the demonstration of improvements in video QoE.

Outline

- Motivation

➔ Data-driven Observations

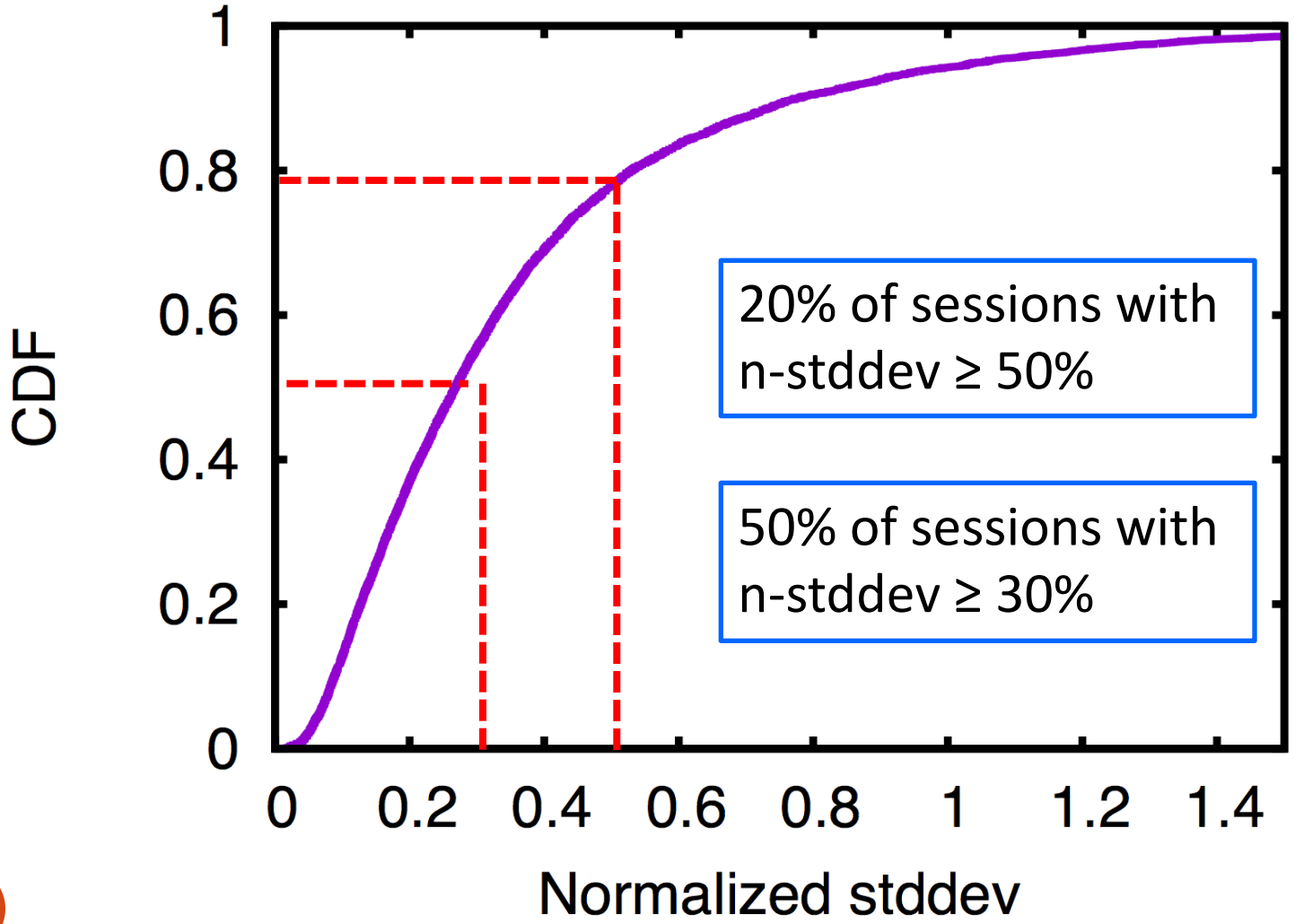
- CS2P Approach
- Evaluation

Dataset description

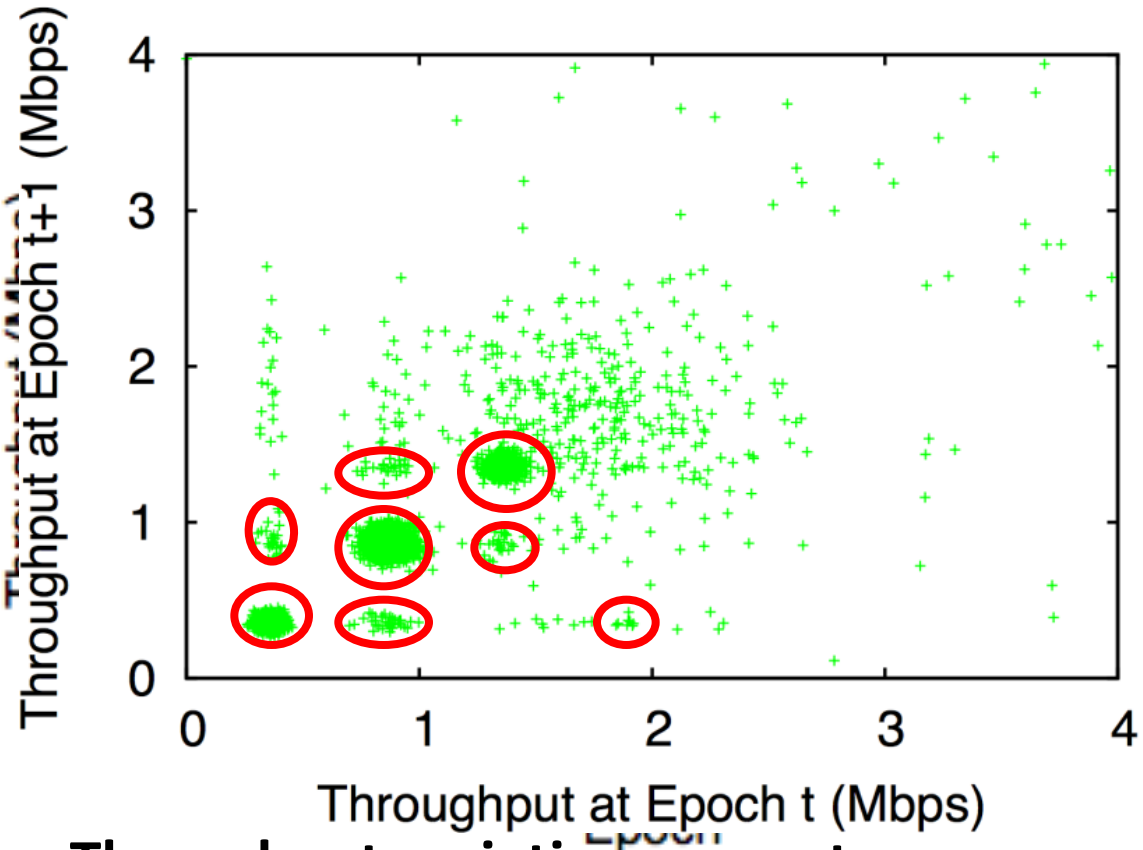
- From operational platform of ***iQIYI***.
  - iQIYI is a leading online video content provider in China.
- ***20M+*** sessions, 8 days in Sep. 2015,
  - Each session records avg. throughput per 6-second **epoch**.

Feature	Coverage
Client IP	3.2M
Client ISP	87
Client AS	161
Province	33
City	736
Server	18

Observation 1:
Significant variability within a session.



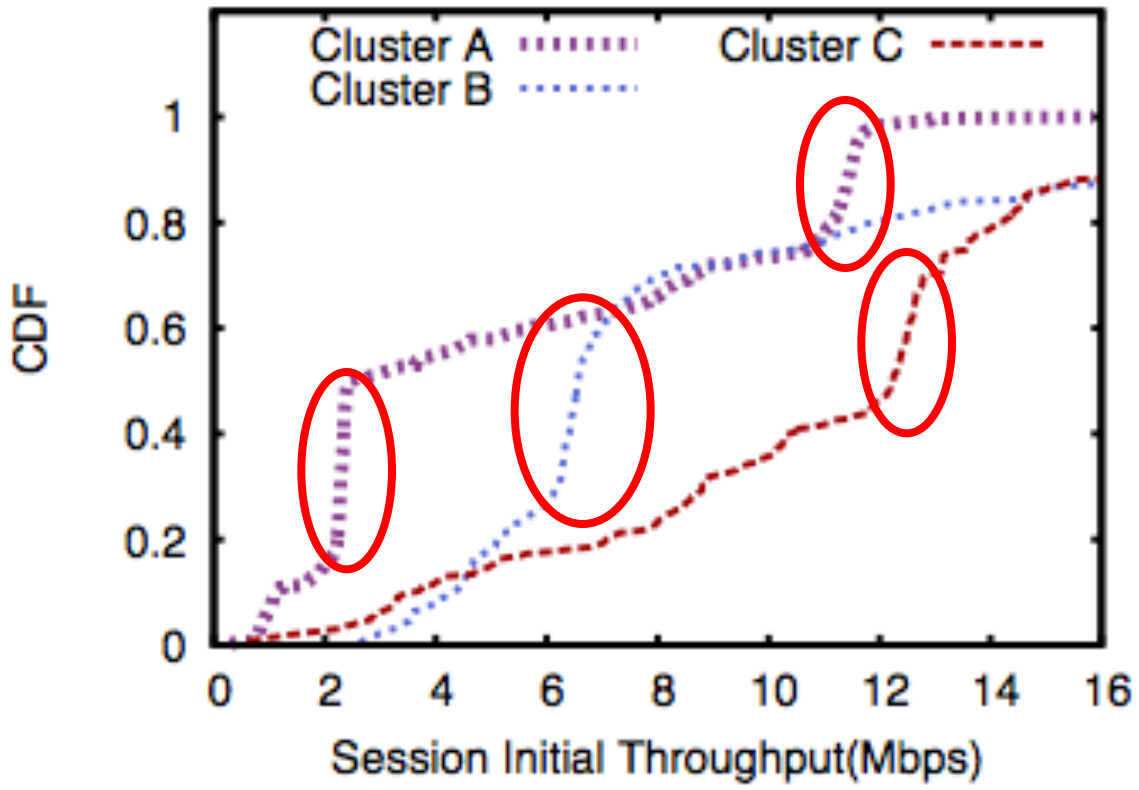
Observation 2: Stateful/persistent characteristics.



Throughput variation across two consecutive epochs with a particular IP/16 prefix.

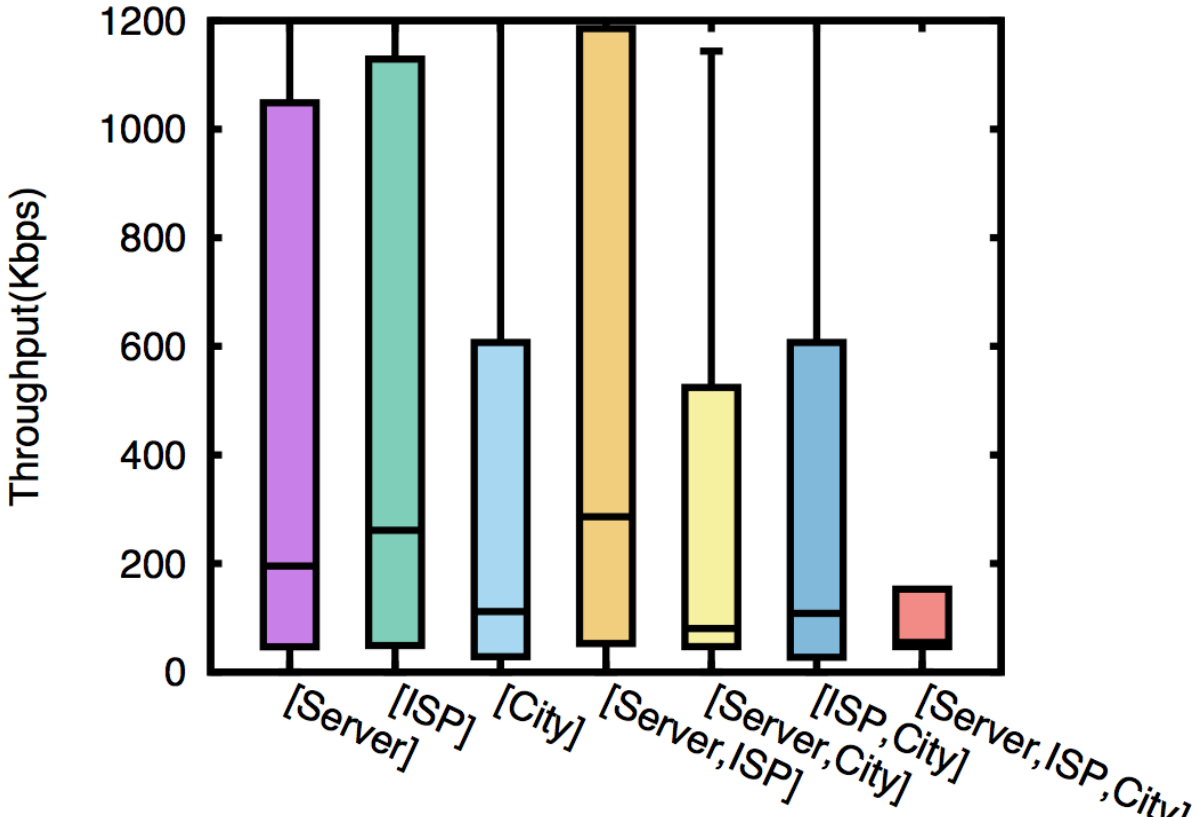
An example session

Observation 3:
Similar session → Similar throughput



Throughput at different session clusters with particular IP/8 prefixes.

Observation 4: Complex relationship between session feature ⟷ throughput



The impact of the same feature on different sessions could be variable.

Combinations of multiple features often have a much greater impact than the individual feature.

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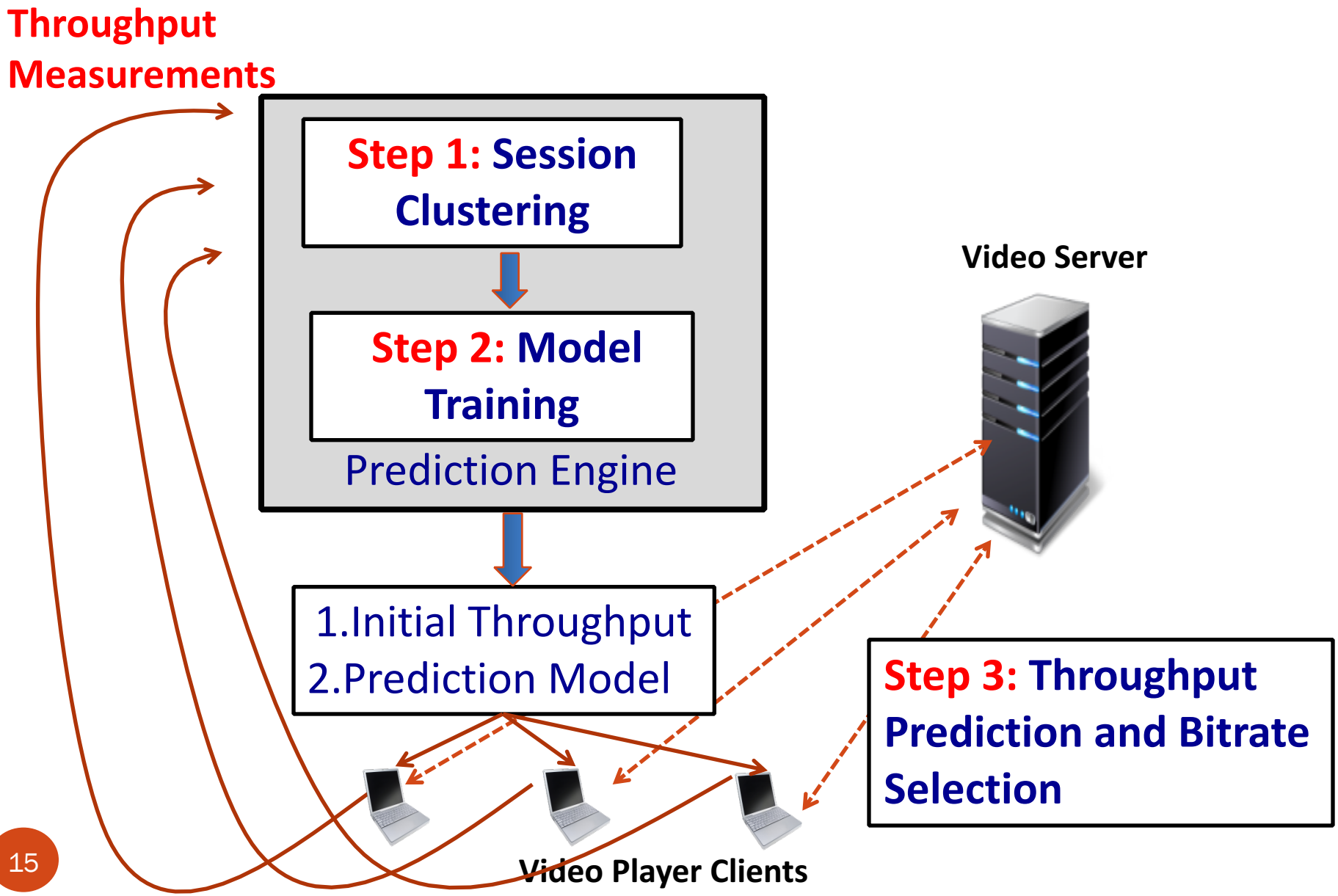
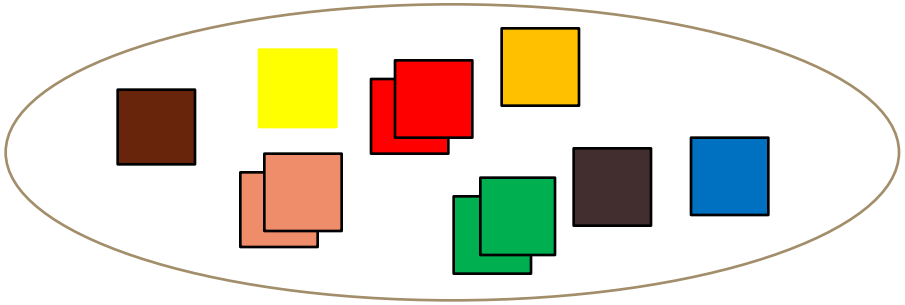
Observation	Idea

Workflow of CS2P



Session clustering-finding critical features



All the sessions for training

Session under prediction

A given subset of session features

Try another session feature subset

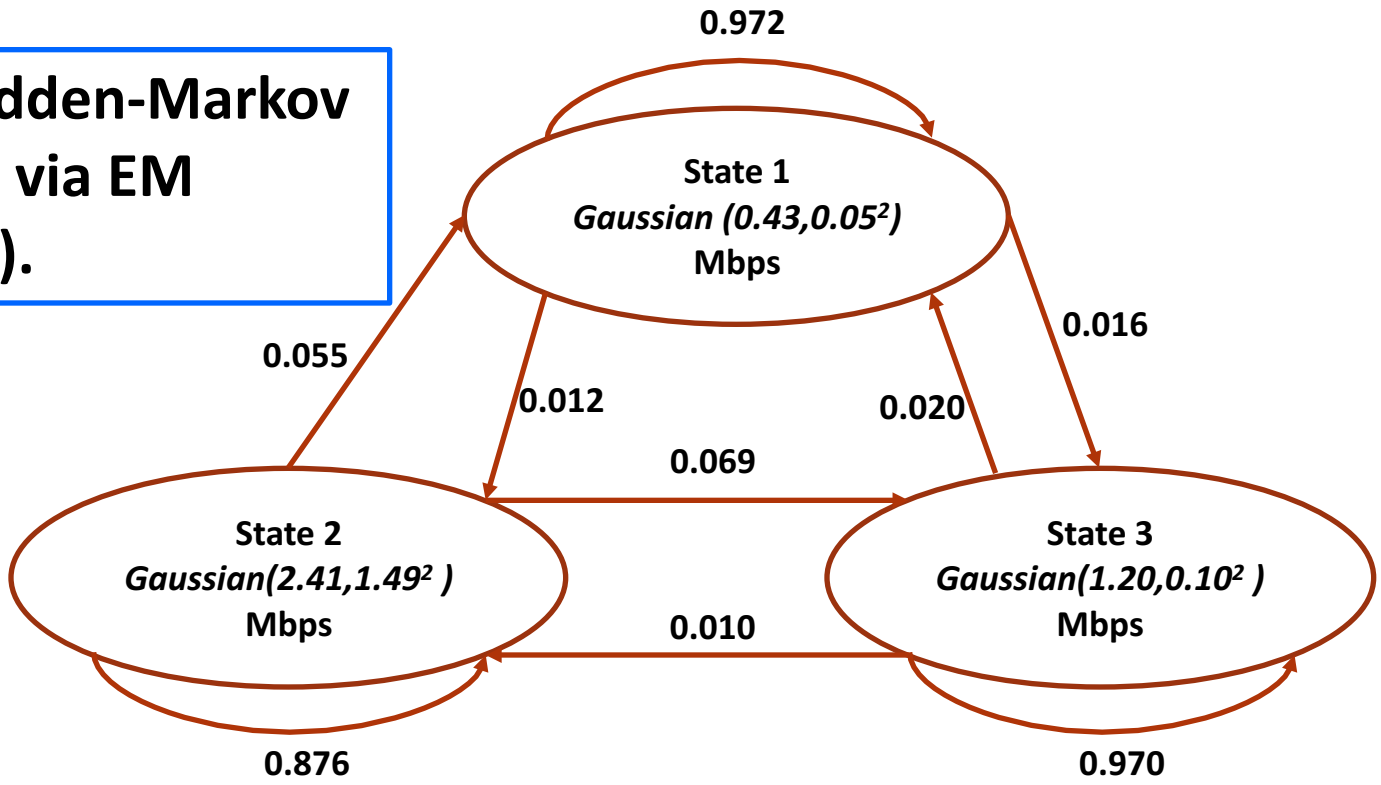
Sessions matching selected features with

Repeat these procedures to find the critical feature , which yields the most accurate throughput prediction of

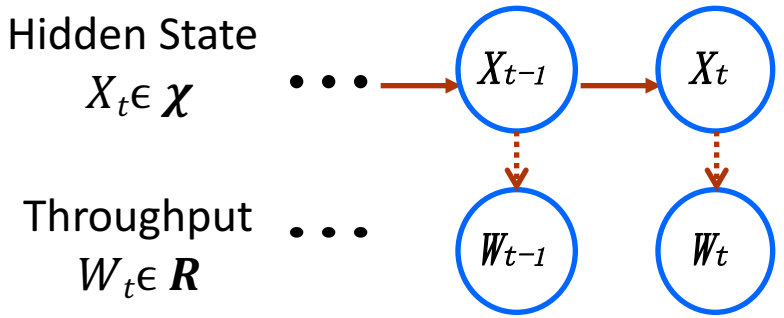
Predict the throughput of with these filtered sessions

Throughput prediction with HMM

Model Train: A Hidden-Markov Model per cluster via EM algorithm (offline).



Throughput prediction and bitrate selection (online).



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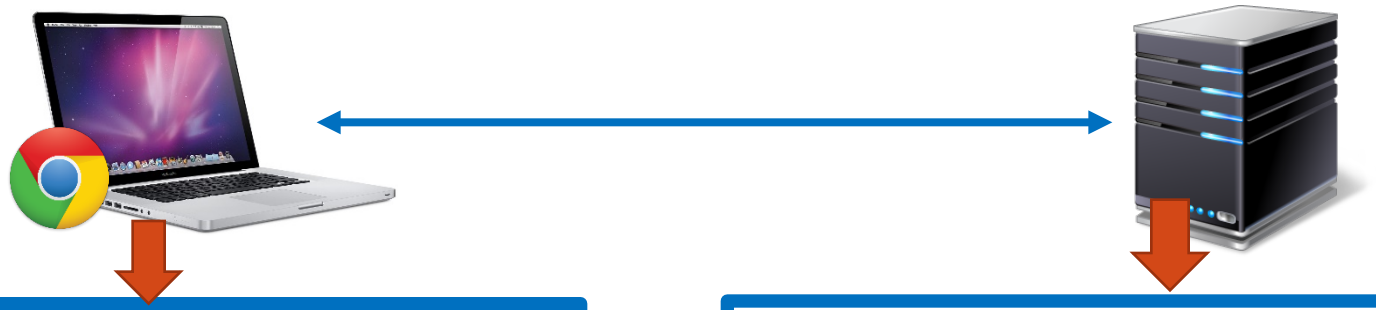
➔ Evaluation

Trace-driven simulation setup



Algorithms to compare:

1. *History-based predictor:*
   - *Last Sample, Harmonic-Mean, Auto Regression*
2. *ML-based predictor:*
   - *SVR, Gradient Boosting Regression trees*
3. *CFA[1]*

Bitrate selection method:

- *State-of-art: MPC[2]*

iQIYI throughput trace:

- *Non-overlapping traces of training and testing*

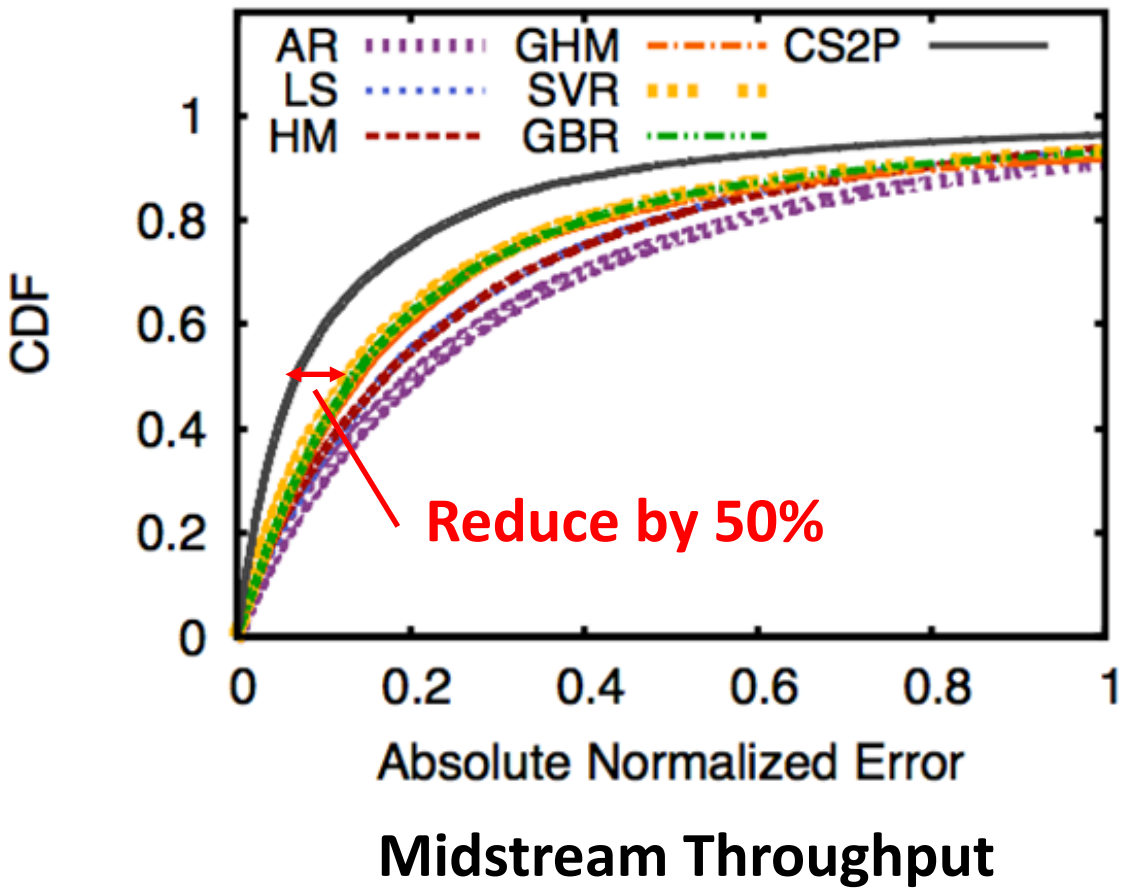
Video source:

- *"Envivio" from dash.js test website*
- *Encoded in H.264/MPEG-4 in 5 bitrate levels*

[1] J. Jiang, et al. "CFA: A Practical Prediction System for Video QoE Optimization". In *Proc.* of *USENIX NSDI, 2016*.

[2] X. Yin, et al. "A Control-Theoretic Approach for Dynamic Adaptive Video Streaming over HTTP". In *Proc.* of *ACM SIGCOMM, 2015*.

Throughput Prediction Accuracy



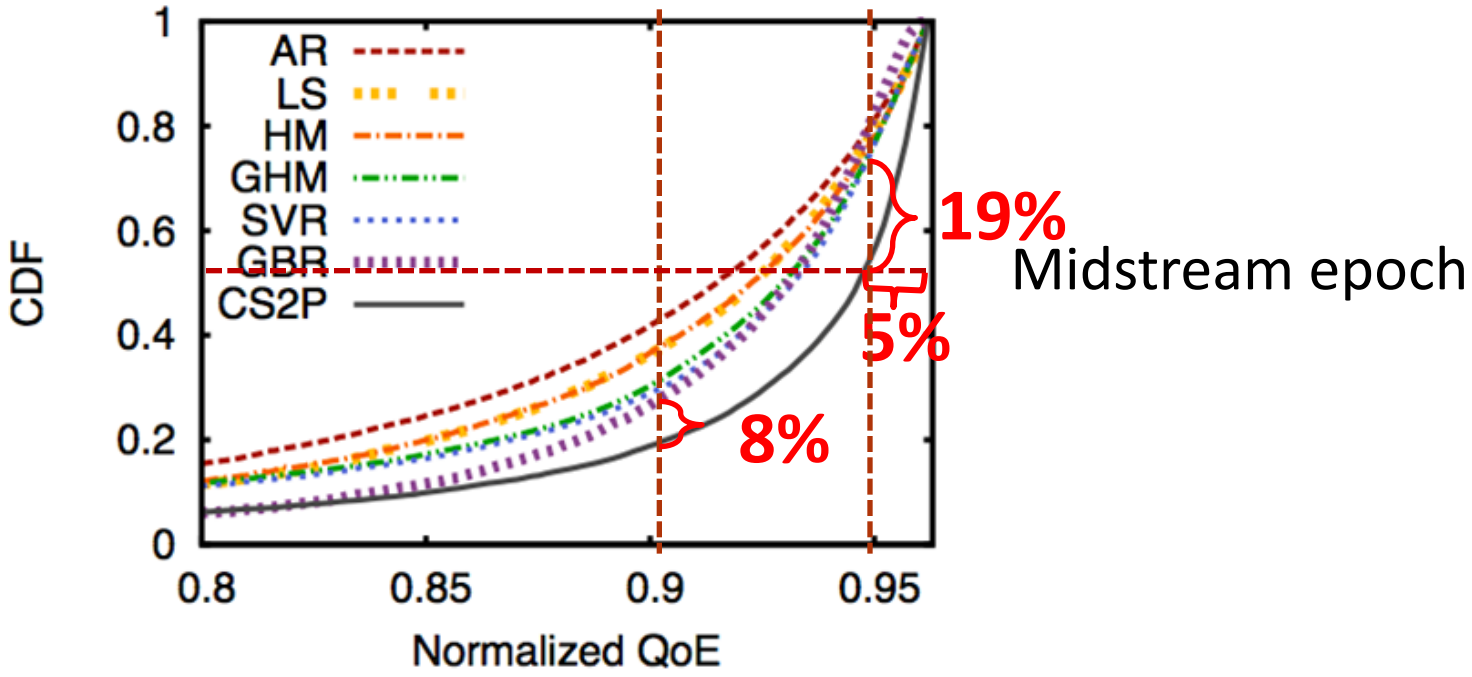
Midstream Throughput

Takeaway

- Midstream Epoch
  - Reduce median error by 50%
- Multi-epoch Ahead
  - 9% prediction error for 10 epoch ahead
  - 50% improvement

Video QoE

- $Normalized\ QoE = \frac{Actual\ QoE}{Theoretical\ \text{optimal}}$
- QoE[1] is a linear combination of avg. video quality, quality variation, total rebuffer time and startup delay.



[1] X.Yin, et al. "A Control-Theoretic Approach for Dynamic Adaptive Video Streaming over HTTP". In *Proc.* of *ACM SIGCOMM, 2015*.

Pilot deployment: multi-city test

Metrics	vs. HM+MPC	vs. BB
Avg. Bitrate	10.9%	9.3%
Good Ratio	2.5%	17.6%
Bitrate Variability	-2.3%	5.6%
Startup Delay	0.4%	-3.0%
Overall QoE	***3.2%***	***14.0%***

Takeaway:

1. CS2P improves most of the QoE metrics, except longer startup delay than BB and higher bitrate variability than HM.
2. The overall QoE improvement of CS2P is 3.2% to HM and 14% to BB.

Conclusions

- Good prediction → Better bitrate selection & adaptation → Improved video QoE

- Key insights on throughput variability
  - Evolution of intra-session throughput exhibits stateful characteristics.
  - Similar sessions have similar throughput structures.

- CS2P: Cross-session HMM-based approach
  - Outperform prior predictors by 50% in midstream prediction error.
  - Achieve 3.2% improvement to HM and 14% to BB in video QoE.