PARSEC: Streaming 360° Videos Using Super-Resolution

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360° Video Streaming

- Central to many immersive applications (e.g., VR/AR)

Image credit: Oculus

Immersive Experience

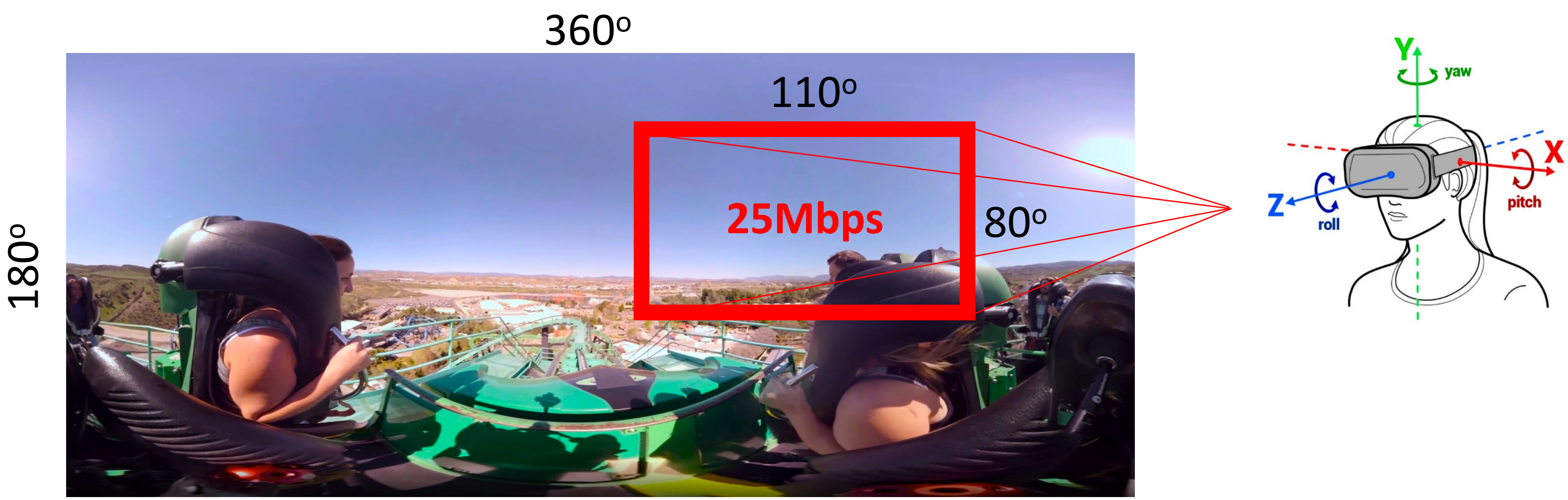
$ Billion Market

Popularity of 360° Video is on the Rise!

http://blog.dsky.co/tag/head-tracking/

Grand Challenge

- 360° videos require 8x bandwidth compared to regular videos for the same perceived quality



200Mbps

Image from Rollercoaster video

http://blog.dsky.co/tag/head-tracking/

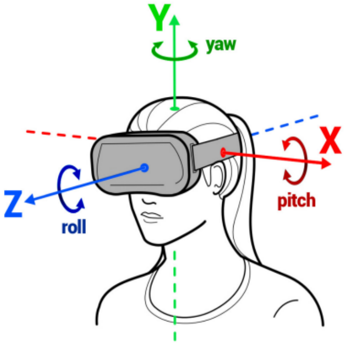
Current Solutions

❑Viewport-adaptive streaming
- Divide video into tiles (e.g., 192x192 pixels)

Flare [MobiCom’18], Rubiks [MobiSys’18], MOSAIC [IFIP Networking’19]
PANO [SIGCOMM’19], ClusTile [INFOCOM’19]

Current Solutions

❑ Viewport-adaptive streaming
  - Divide video into tiles (e.g., 192x192 pixels)
  - Predict viewport tiles based on head tracking and video saliency analysis
  - Stream only viewport specific tiles using ABR algorithm



Flare [MobiCom’18], Rubiks [MobiSys’18], MOSAIC [IFIP Networking’19]
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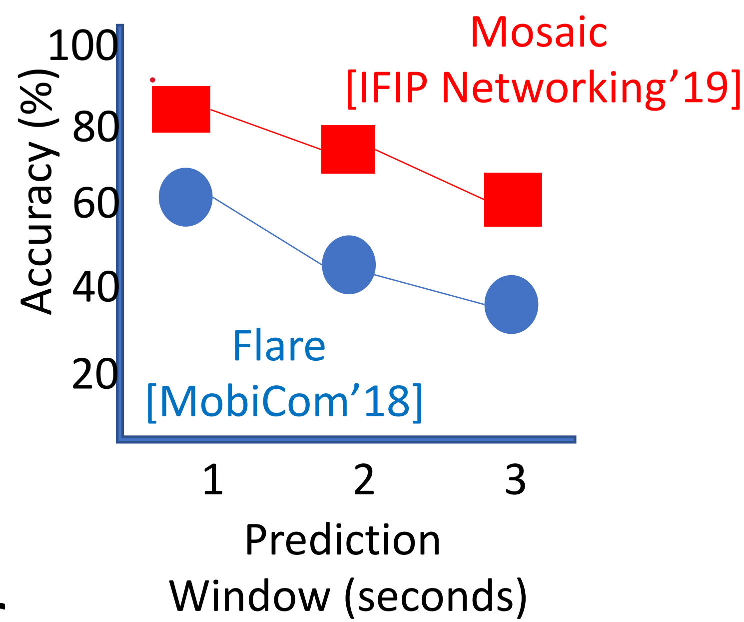
Limitations of Current Solutions

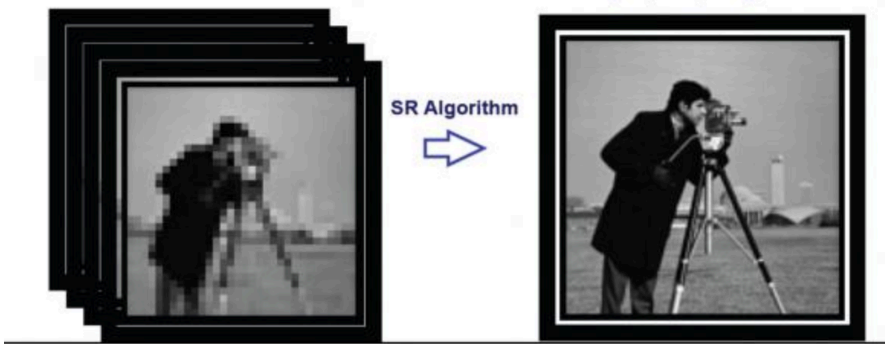
- ❑ Viewport Prediction (VP)
  - Predicting user head movement is hard
  - Fetch more tiles to avoid the tile misses
  - Fetching more tiles competes for bandwidth and reduces video quality
- ❑ Network is the only resource for achieving good video quality



Can we improve client's video quality without relying much on network?

Opportunity1: Super-resolution

❑ Use low resolution image/video, hallucinate the details to produce high resolution



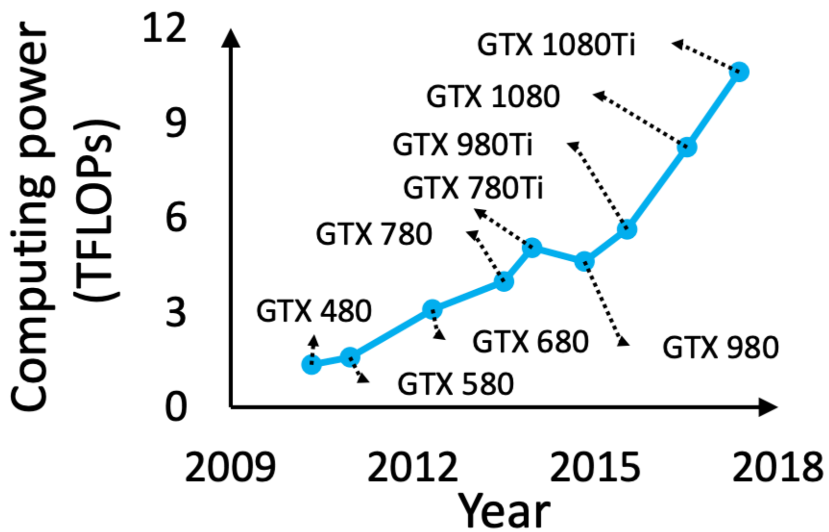
https://amundtveit.com/2017/06/04/deep-learning-for-image-super-resolution-scale-up/

- Idea dates to the 90s
- Currently benefiting from deep neural networks (DNNs)

DNNs are computationally expensive

Opportunity2: Computation

- ❑Significant improvement in GPU capacity over the decade
  - Often underutilized
- ❑Leverage this compute capacity on the client to do super-resolution

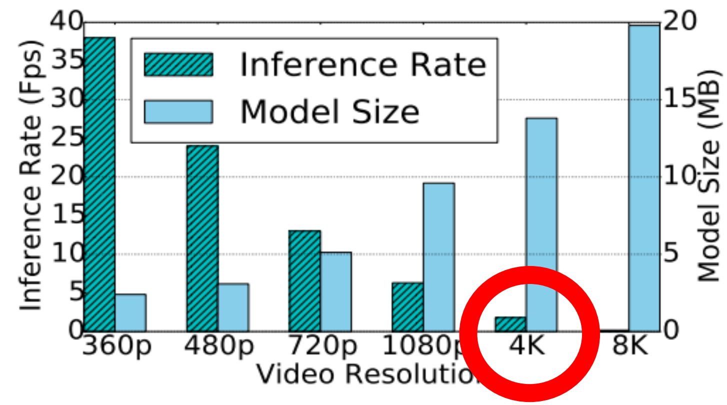


NAS [OSDI'2018]

Is this compute power enough to do super-resolution?

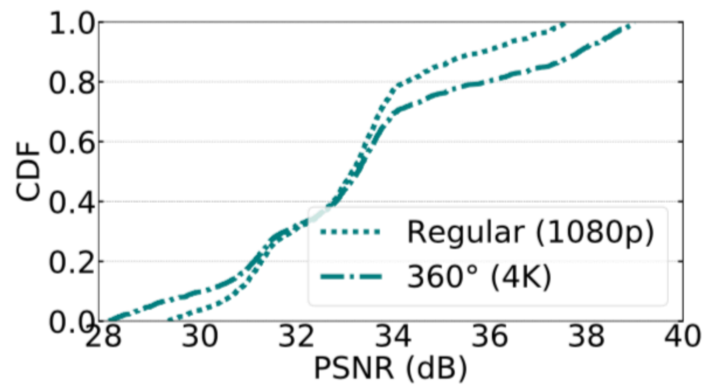
Super-resolution Challenges

- ❑ Bulky DNN models
  - Slower inference (e.g., less than 2FPS for a 1-minute 4k video)
  - Large model sizes



Model trained for one-minute video duration

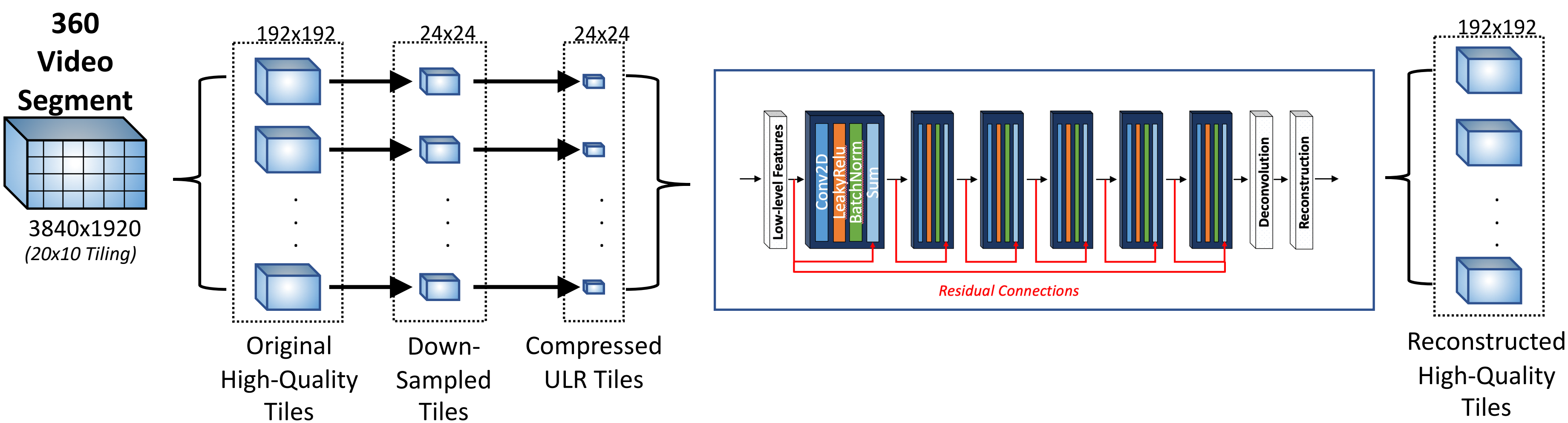
- ❑ Large variance in quality enhancement



How to make the models smaller, faster & better?

Lightweight Micro-models for Super-resolution

- ❑Train a model for each segment



- ❑Fetch the model along with segment download
- ❑Enhance the quality of few viewport-specific tiles instead of whole frame

Lightweight Micro-models for Super-resolution

❑ Benefits

✓ Small model footprint

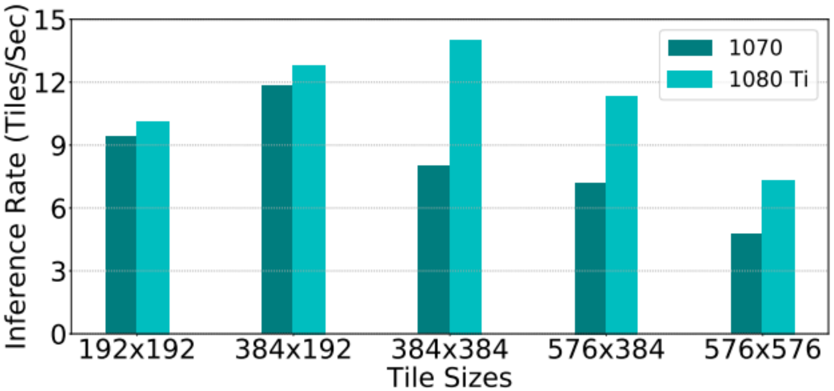
✓ Faster inference

❑ Key Questions

- Which tiles to download and at what quality?
- Which tiles to generate (using super-resolution)?
- Which tiles to ignore?

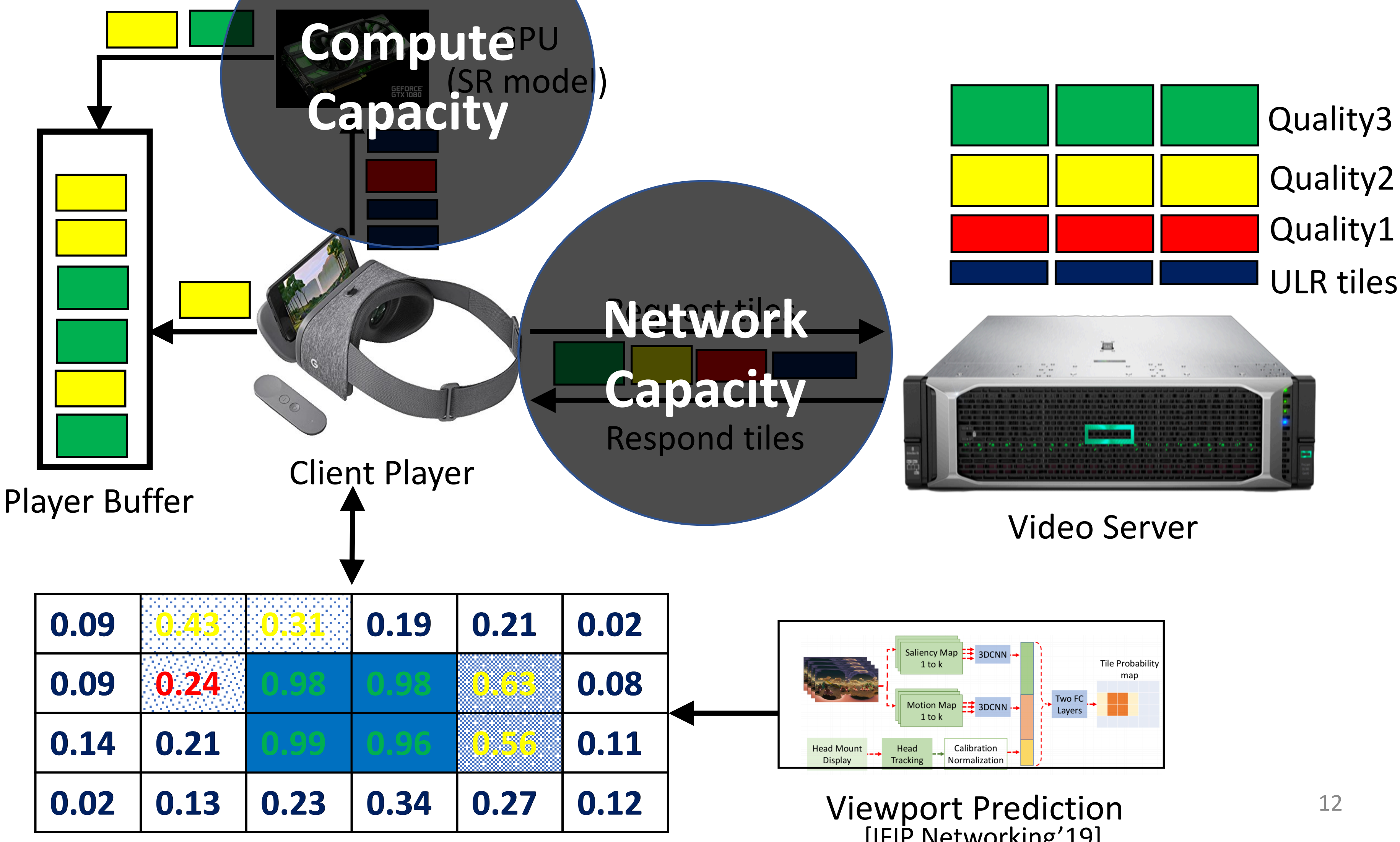
❑ Additional challenges

- Still only few tile/sec inference rate



Need a new ABR algorithm that combines compute and network resources

Neural-Aware ABR



0.09	0.43	0.31	0.19	0.21	0.02
0.09	0.24	0.98	0.98	0.63	0.08
0.14	0.21	0.99	0.96	0.56	0.11
0.02	0.13	0.23	0.34	0.27	0.12

Neural-Aware ABR

Expected Quality $E(Q) = \sum_{i=1}^{N} p_i (q_{i,D} r_{i,D} + q_{i,G} r_{i,G})$

Download ULR and enhance using SR

Tile miss ratio $E(M) = \sum_{i=1}^{N} p_i r_{i,M}$

Pure download

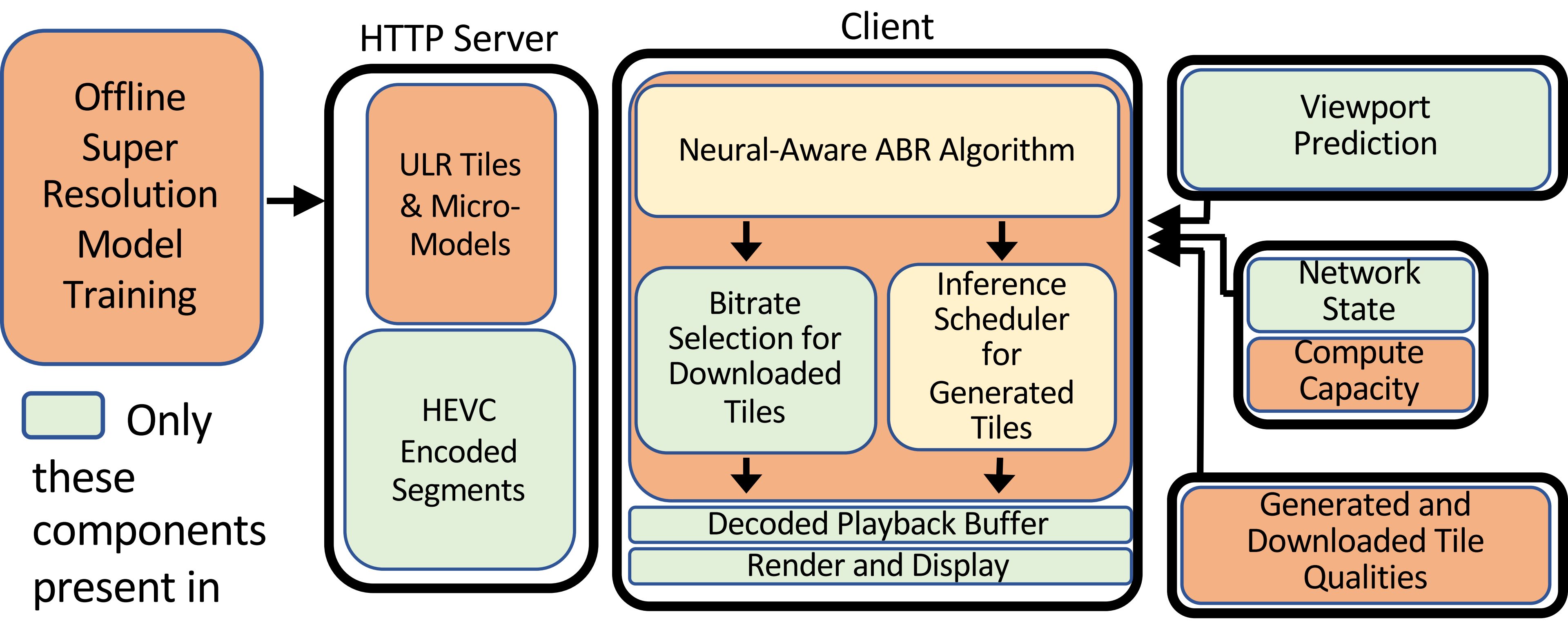
How to Find a Solution Fast?

Greedy Algorithm

Quality switches $V_s = \sum_{i=1}^{N} \mathrm{StdDev}[p_i (q_{i,D} r_{i,D} + q_{i,G} r_{i,G})]$

Overall experience $\boxed{QoE = E(Q) - \beta E(M) - \xi (V_s + V_t)}$ Maximize

Putting Everything Together



Only these components present in state-of-the-art 360° video streaming

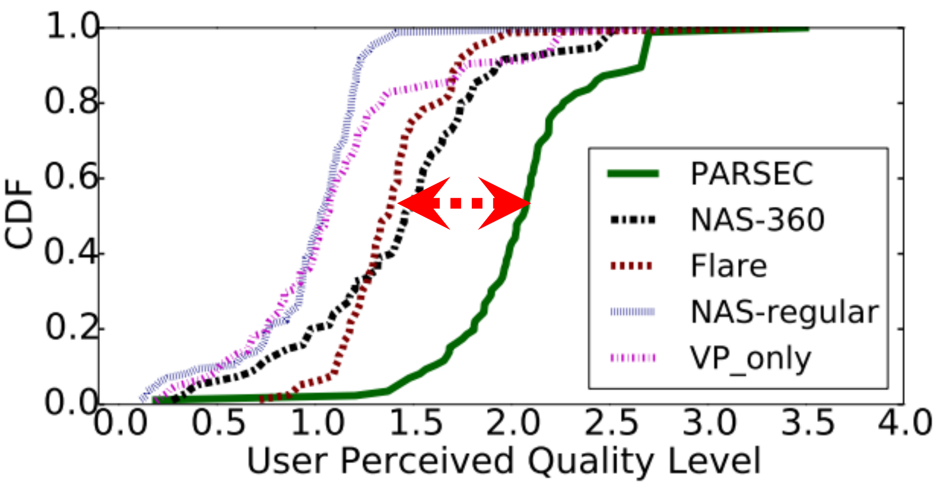
Implementation & Evaluation

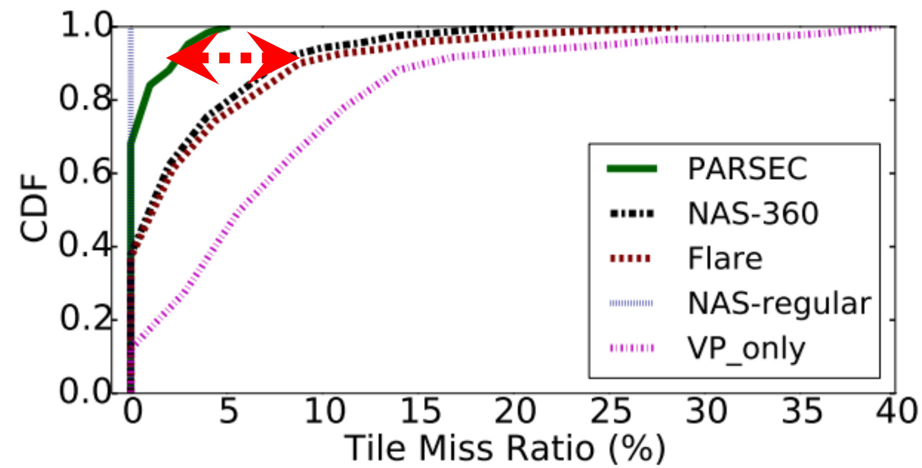
- Linux server
  - Node.js
- Client
  - Pixel3 phone
- Super-resolution model
  - Keras with Tensorflow backend
- Diverse network conditions
  - Real traces: WiFi & 4G/LTE
  - FCC & Belgium traces
- 360^{o} video dataset
  - 10 videos
  - MMSYS’17 head movement dataset

Performance Comparison

- VP_Only [NOSSDAV'17]
  - Download only viewport-specific tiles
- FLARE [MobiCom'18]
  - Fetch additional tiles to accommodate VP inaccuracy
- NAS-regular [OSDI'18]
  - A recent regular video streaming system using super-resolution
- NAS-360
  - A modified version of NAS-regular for 360^o video

Performance Comparison
Average Quality and Tile Misses

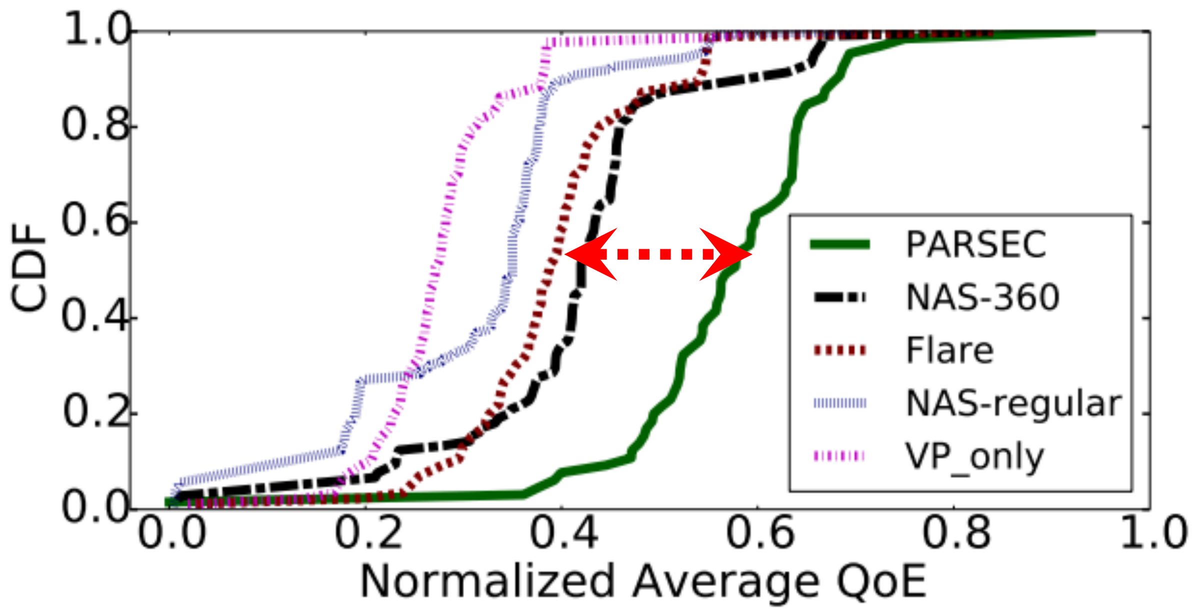




30% improvement compared to Flare [MobiCom'18]

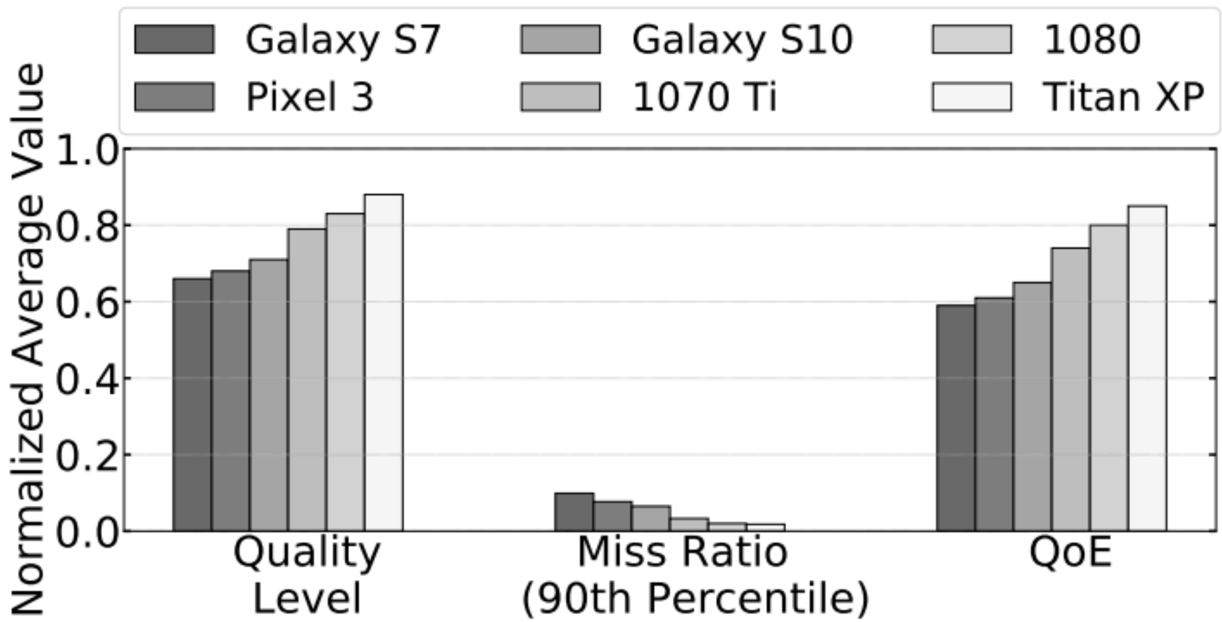
26% improvement at the 90th percentile compared to Flare [MobiCom'18]

Overall QoE Performance



37% improvement compared to Flare [MobiCom'18]

Impact of Computation



PARSEC performs better as we increase the computing power

Conclusion

- PARSEC
  - A panoramic video streaming system
  - DNN based super-resolution
  - Neural-aware ABR algorithm
- PARSEC provides high QoE compared to the state-of-the-art solutions

For more details please visit:

https://www3.cs.stonybrook.edu/~mdasari/parsec