Live Video Analytics at Scale with Approximation and Delay-Tolerance

Haoyu Zhang, Ganesh Ananthanarayanan, Peter Bodik,
Matthai Philipose, Paramvir Bahl, Michael J. Freedman

PRINCETON UNIVERSITY

Microsoft

Video cameras are pervasive

TECHNOLOGY | Fri Jun 21, 2013 | 11:24am EDT

NYPD expan…
fight crime a…

By Chris Francescani | NEW YOR…

Having developed one of the…
States, the New York Police D…
commanders new powers to…
in counterterrorism operation…

"The technology, having beer…
9/11, has obvious application…
NYPD spokesman. "That is in…
all - is our primary mission, w…

Cameras and IoT: Going from smart
to intelligen…

Posted on July 22, 2016

CATHRINE …
Contributing…

An intelligent video cam…
video content. Events ca…
desired actions. The abi…
what makes the camera…

Imagine the video came…
on the ground. Instead…
place, the intelligent ca…
other necessary assista…
to action.

Microsoft looks to stop bike crashes before they happen, testing Minority Report-style predictive intelligence

BY LISA STIFFLER on October 14, 2015 at 1:00 pm

24 Comments | Share 216 | Tweet | Share 99 | Reddit | Email

Microsoft engineers and City of Bellevue planners have a sci-fi inspired strategy for curbing bike and pedestrian injuries on city streets: By using video analytics, they want to predict and prevent crashes before they happen.

"This is like 'Minority Report,'" said Bellevue senior transportation planner Franz Loewenherz, referring to the 2002 film in which Tom Cruise preemptively stops crime. "We're trying to get out in front of the collisions. We can take a corrective measure before someone gets hurt."

Video analytics queries

Intelligent Traffic System

AMBER Alert

Electronic Toll Collection

Video Doorbell

Video query: a pipeline of *transforms*

- Vision algorithms chained together
- Example: traffic counter pipeline

transform decode → *transform* detect object → *transform* track object → *transform* count object

Video queries are expensive in resource usage

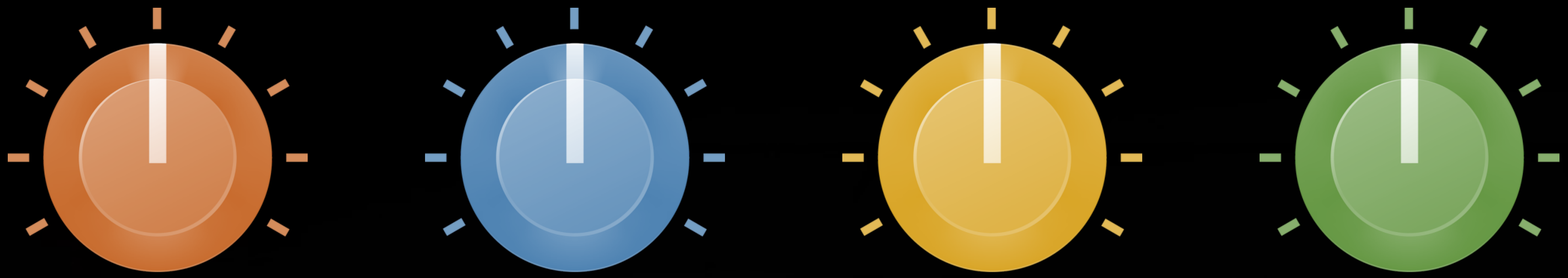
- Best car tracker [1] — 1 fps on an 8-core CPU
- DNN for object classification [2] — 30GFlops

- When processing *thousands* of video streams in multi-tenant clusters
  - How to reduce processing cost of a query?
  - How to manage resources efficiently across queries?

[1] VOT Challenge 2015 Results.
[2] Simonyan et al. CVPR abs/1409.1556, 2014

Vision algorithms are intrinsically *approximate*

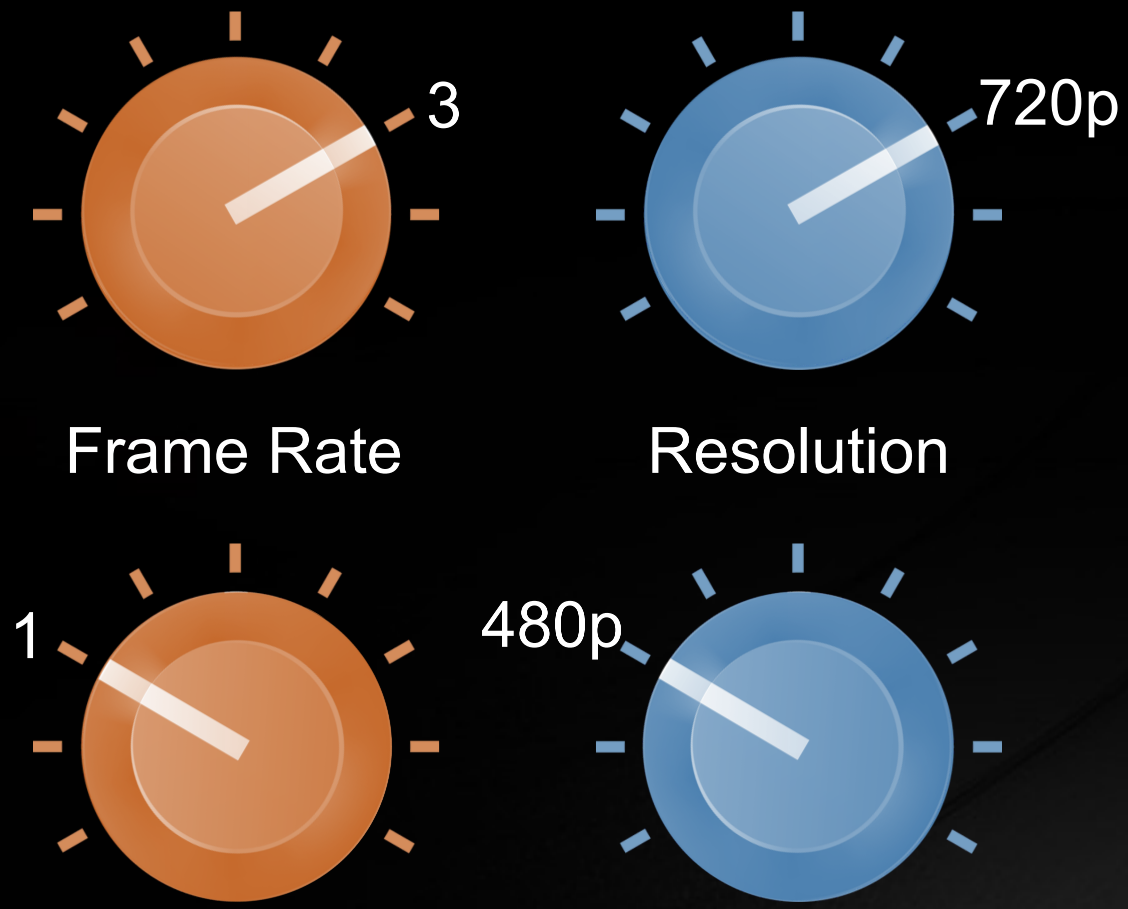
- Knobs: parameters / implementation choices for transforms

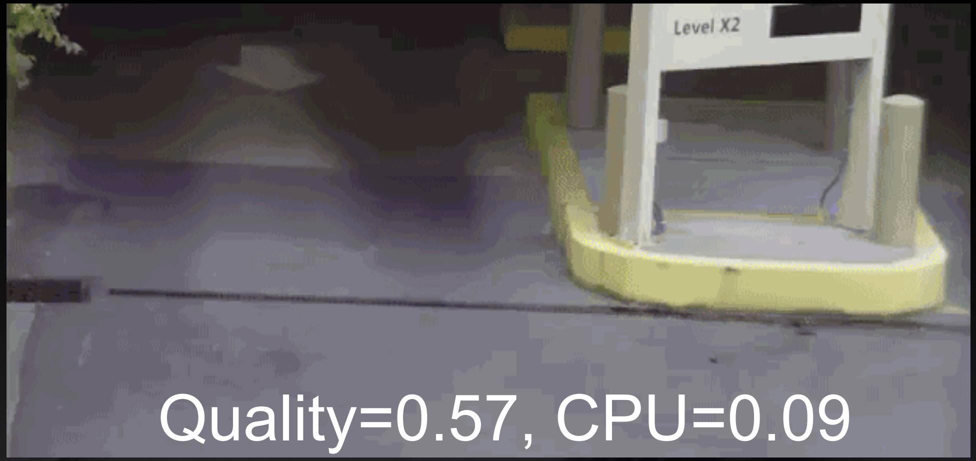


Frame Rate   Resolution   Window Size   Mapping Metric

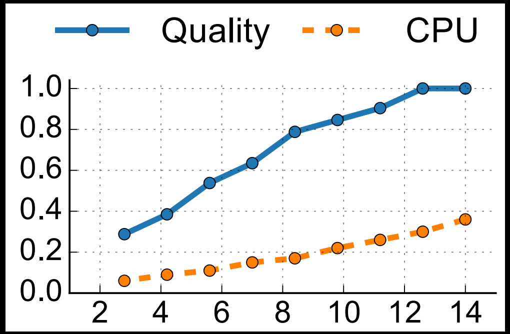
  - License plate reader → window size
  - Car tracker → mapping metric
  - Object classifier → DNN model
- Query configuration: a combination of knob values

Knobs impact quality and resource usage

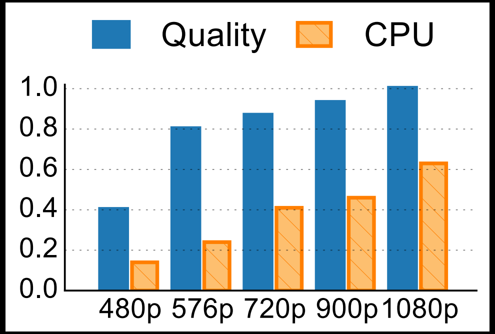




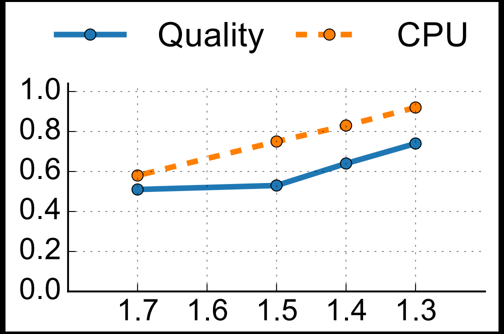
Knobs impact quality and resource usage



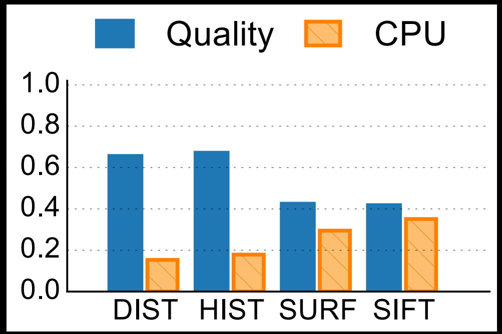
Frame Rate



Resolution

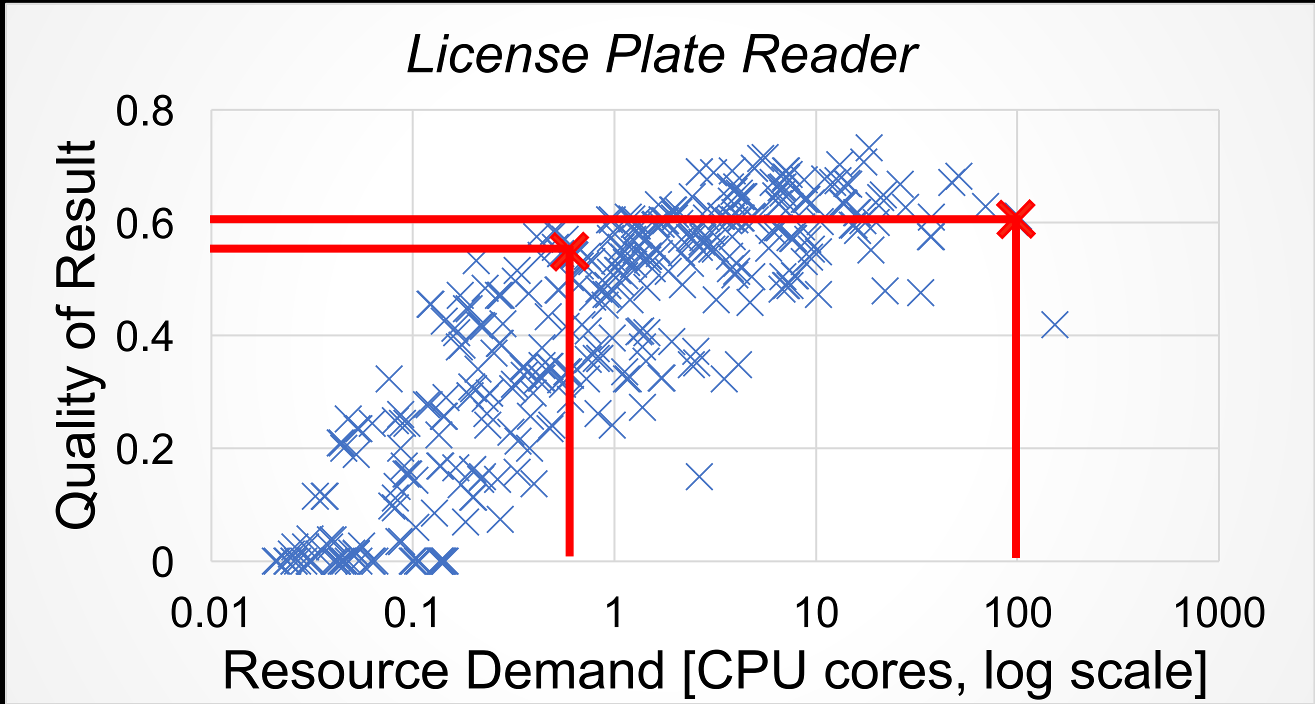


Window Size



Mapping Metric

Knobs impact quality and resource usage



- Orders of magnitude cheaper resource demand for little quality drop
- No analytical models to predict resource-quality tradeoff
  - Different from approximate SQL queries

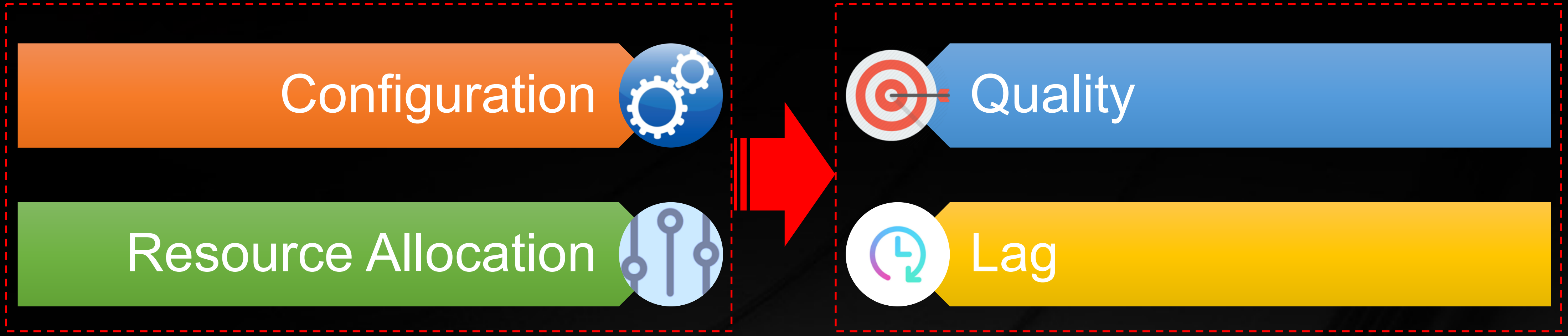
Diverse quality and lag requirements

Lag: time difference between frame arrival and frame processing

	Toll Collection	Intelligent Traffic	AMBER Alert
Quality?	High	Moderate	High
Lag?	Hours	Few Seconds	Few Seconds

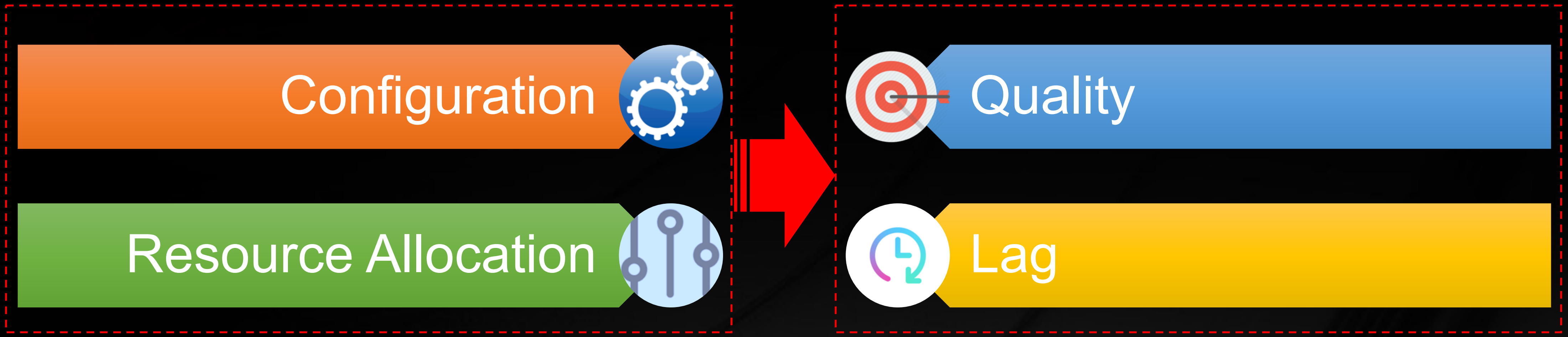
Goal

Decide configuration and resource allocation to maximize quality and minimize lag within the resource capacity

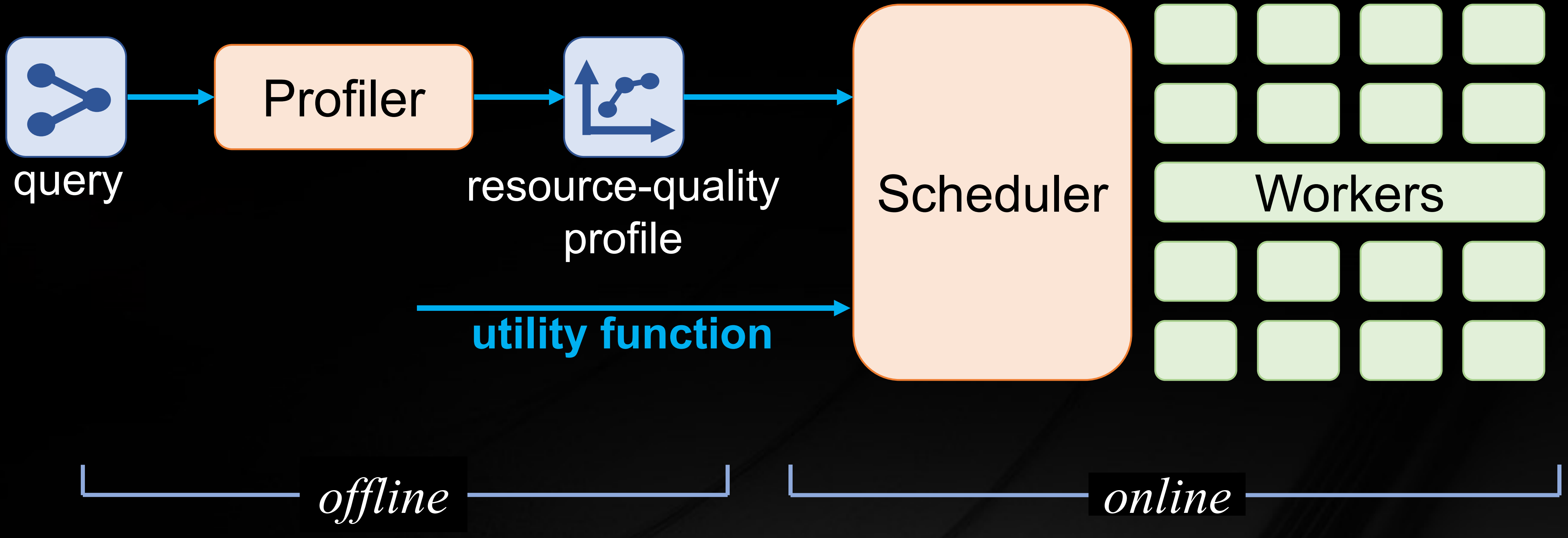


Video analytics framework: Challenges

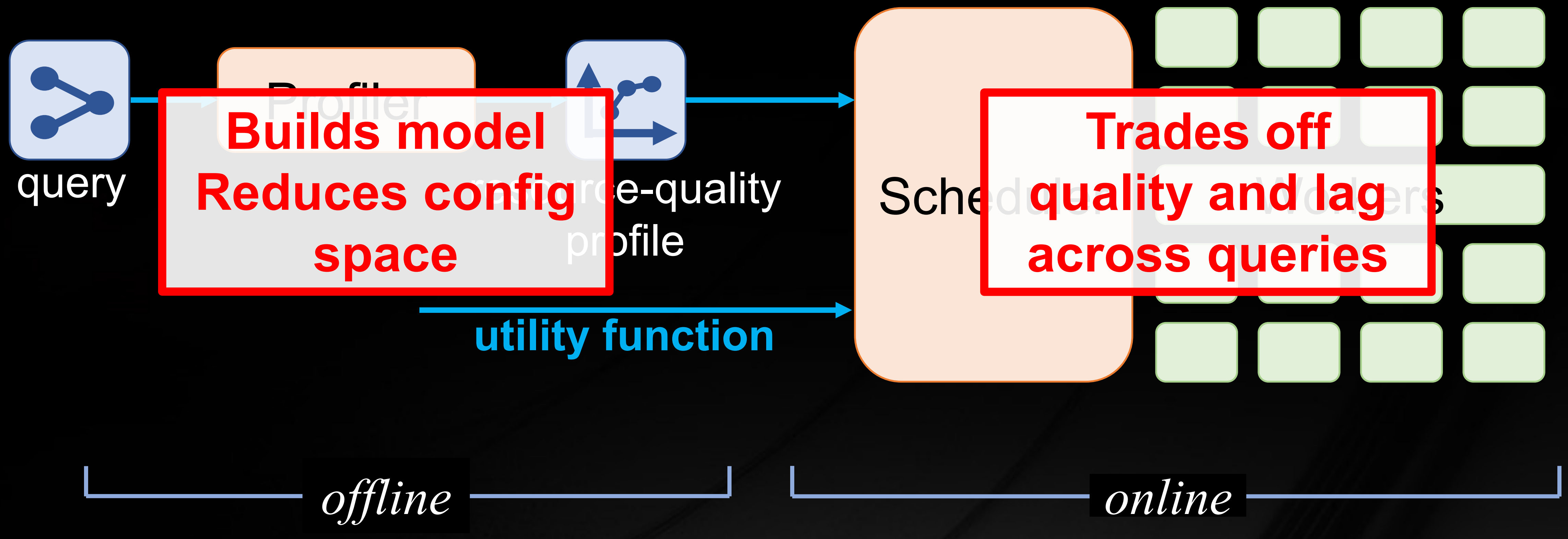
1. Many knobs → large configuration space
   - No known analytical models to predict quality and resource impact
2. Diverse requirements on quality and lag
   - Hard to configure and allocate resources jointly across queries



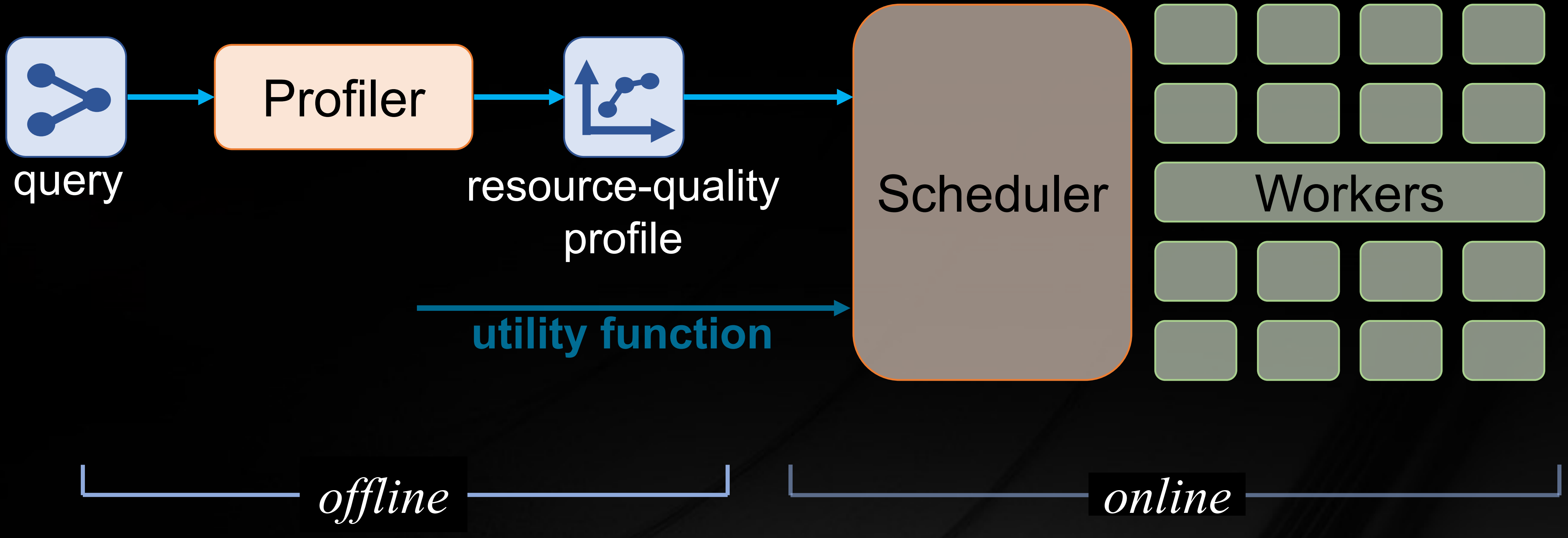
VideoStorm: Solution Overview



VideoStorm: Solution Overview

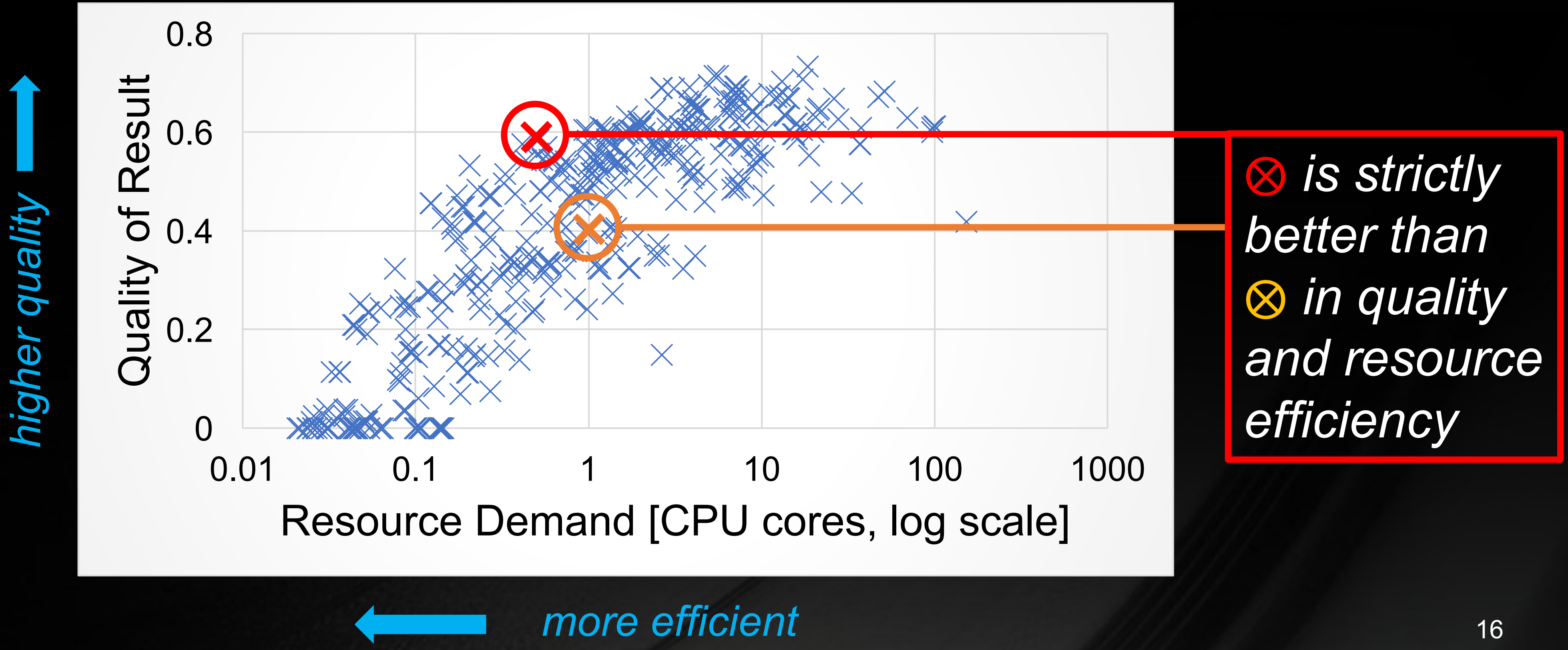


VideoStorm: Solution Overview



Offline: query profiling

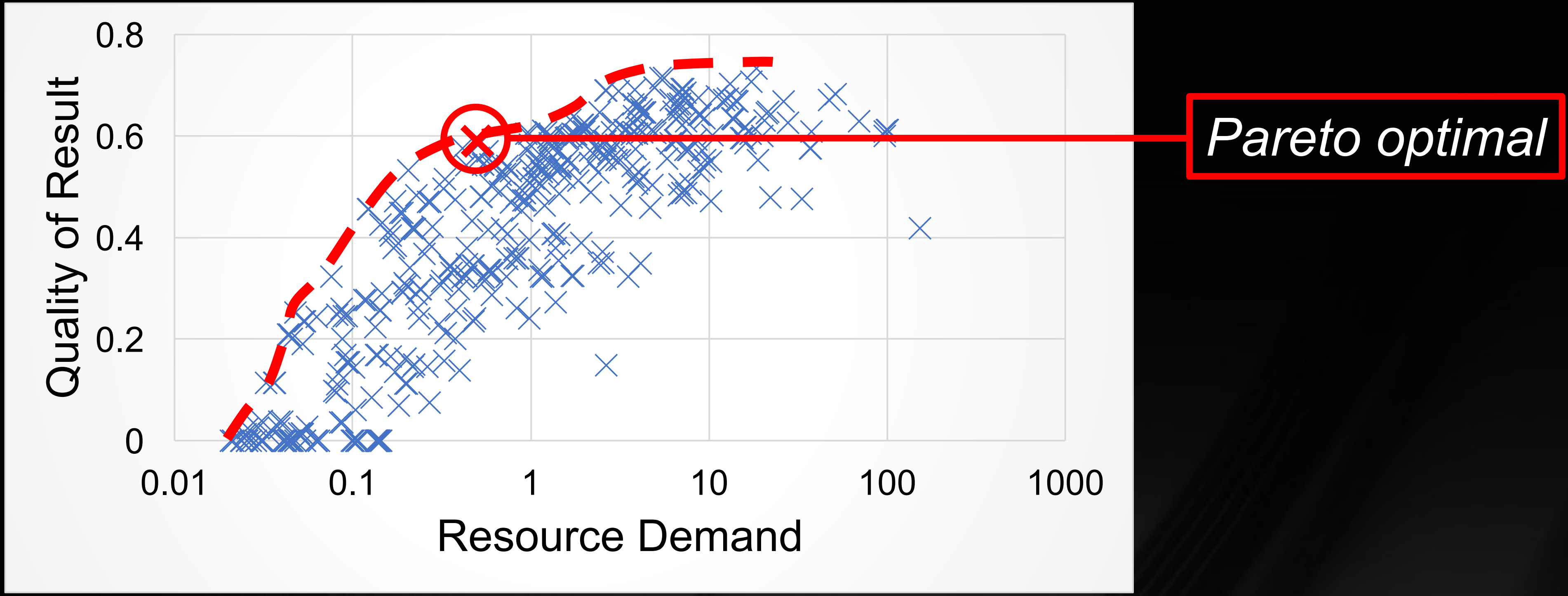
- Profile: configuration ⟹ resource, quality
  - Ground-truth: labeled dataset or results from *golden* configuration
  - Explore configuration space, compute average resource and quality



Offline: Pareto boundary of configuration space

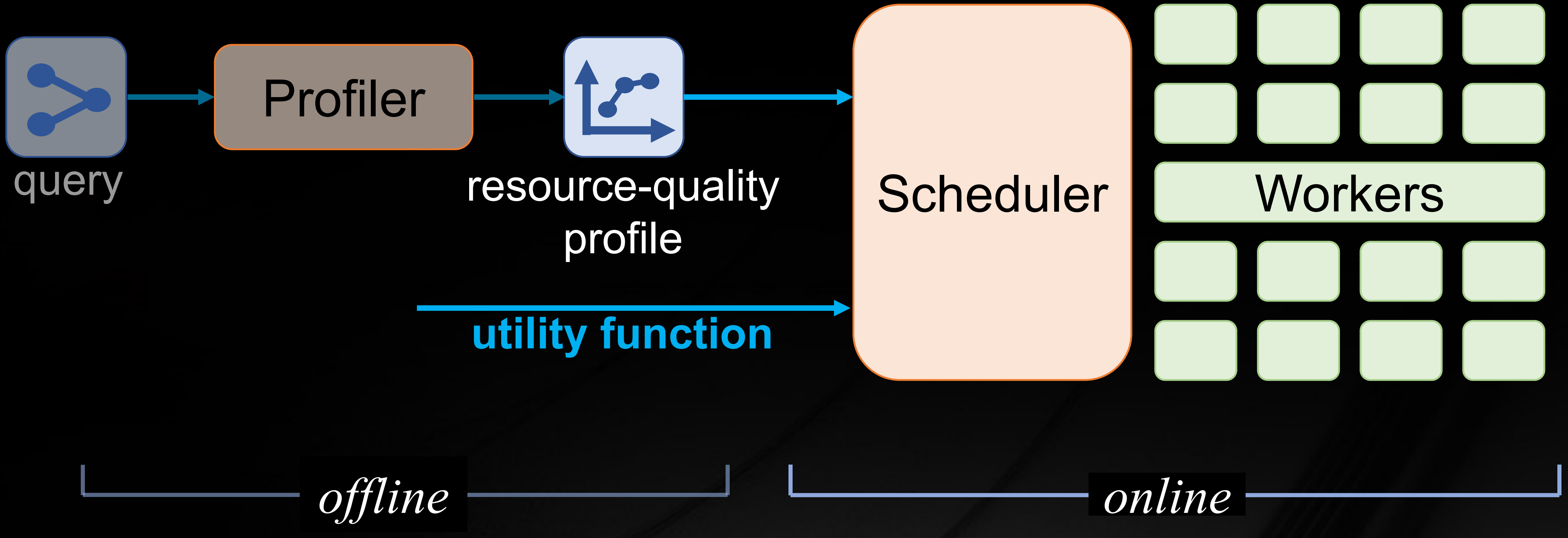
- Pareto boundary: optimal configurations in resource efficiency and quality
  - Cannot further increase one without reducing the other
  - Orders of magnitude reduction in config. search space for scheduling

higher quality



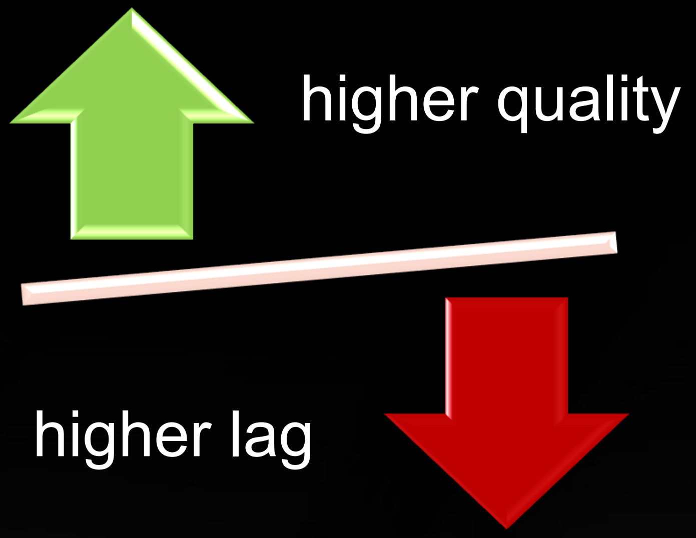
more efficient

VideoStorm: Solution Overview



Online: utility function and scheduling

- Utility function: encode goals and sensitivities of quality and lag
  - Users set required quality and tolerable lag
  - Reward additional quality, penalize higher lag

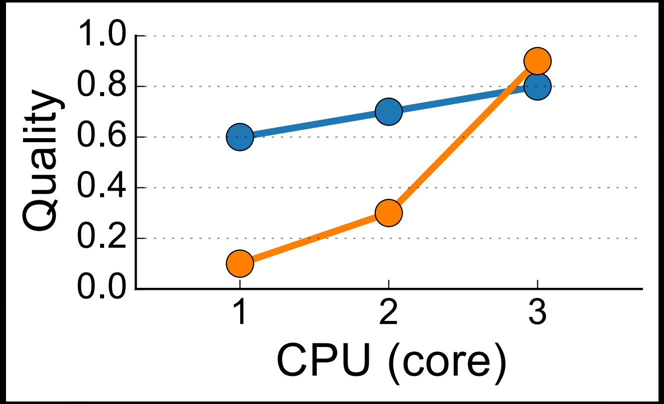


- Schedule for two natural goals:
  - Maximize the minimum utility – (max-min) fairness
  - Maximize the total utility – overall performance

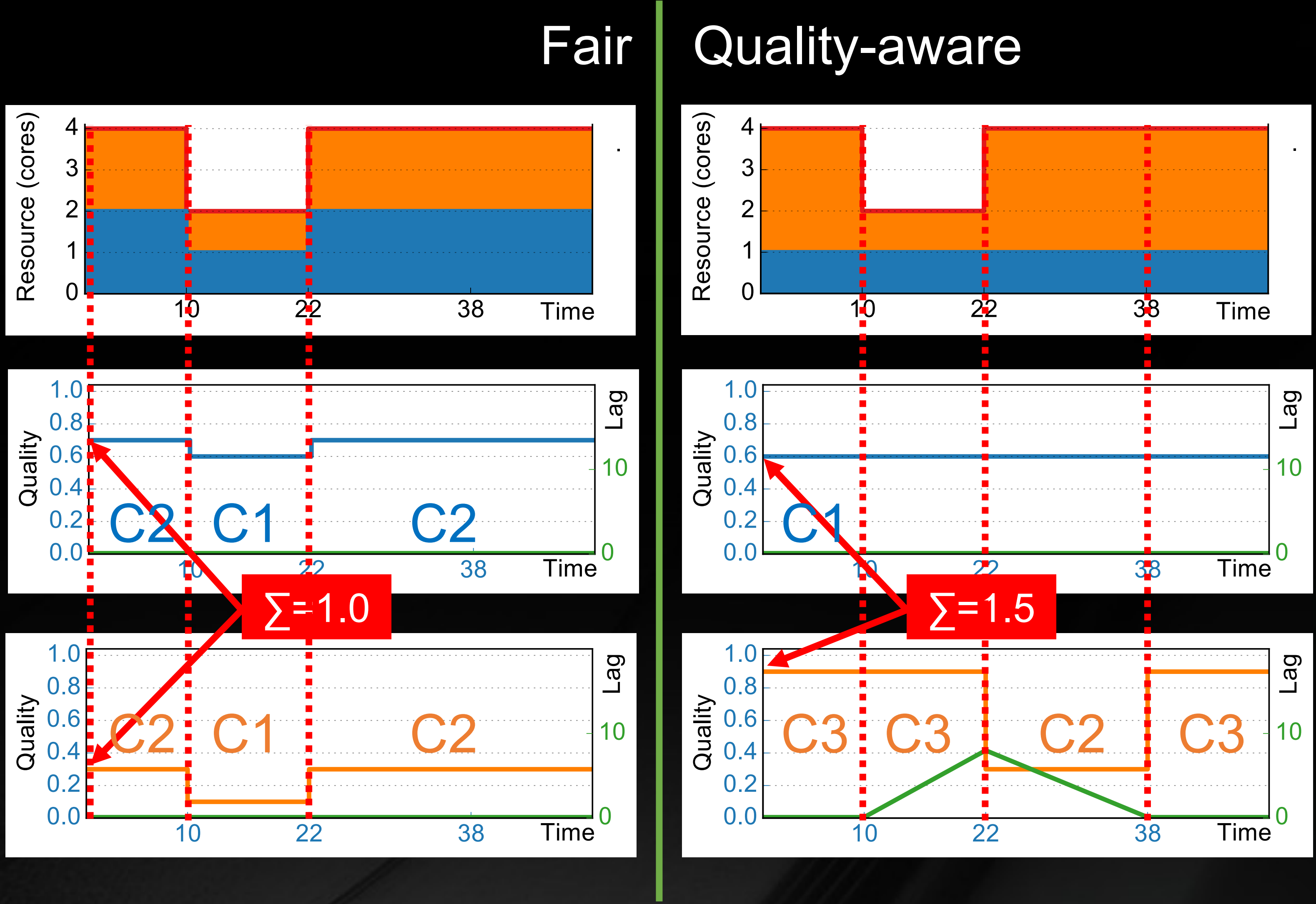
- Allow lag accumulation during resource shortage, then catch up

Online: scheduling approximate video queries

- Queries: blue and orange (tolerate 8s lag)



- Total CPU: 4 → 2 → 4
- Fair scheduler: best configurations w/o lag
- Quality-aware scheduler: allow lag → catch up



Additional Enhancements

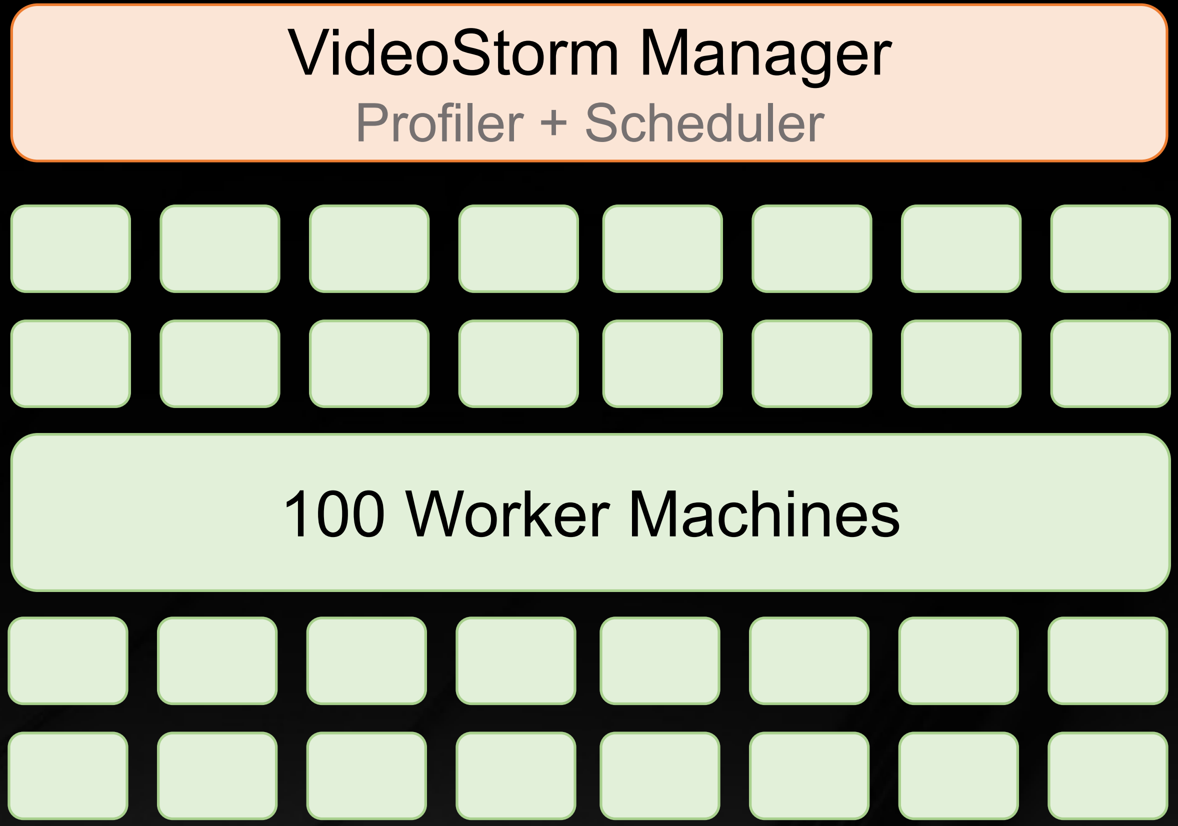
- Handle incorrect resource profiles
  - Profiled resource demand might not correspond to actual queries
  - Robust to errors in query profiles

- Query placement and migration
  - Better utilization, load balancing and lag spreading

- Hierarchical scheduling
  - Cluster and machine level scheduling
  - Better efficiency and scalability

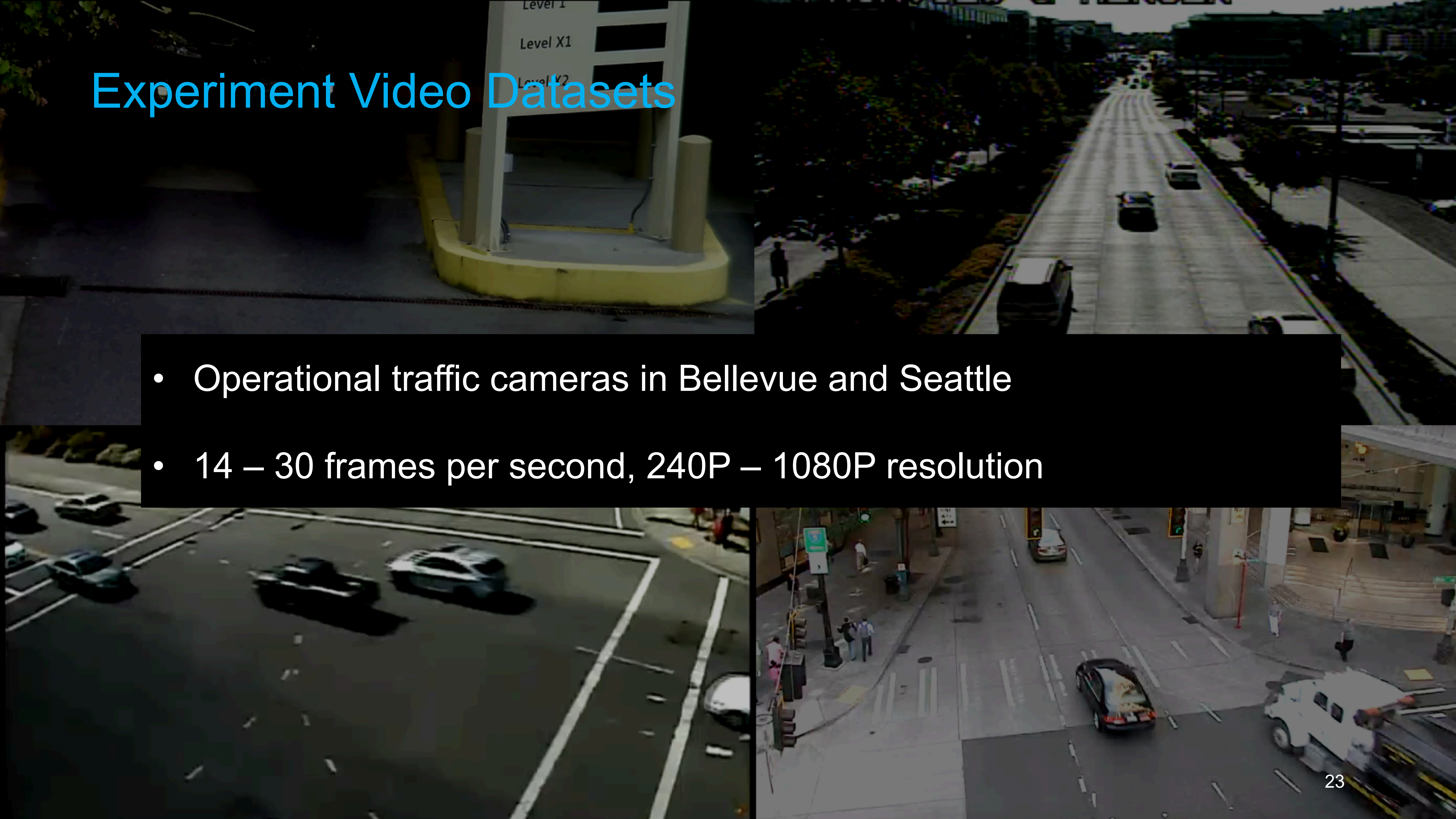
VideoStorm Evaluation Setup

- Platform:
  - Microsoft Azure cluster
  - Each worker contains 4 cores of the 2.4GHz Intel Xeon processor and 14GB RAM
- Four types of vision queries:
  - license plate reader
  - car counter
  - DNN classifier
  - object tracker



Experiment Video Datasets

- Operational traffic cameras in Bellevue and Seattle
- 14 – 30 frames per second, 240P – 1080P resolution

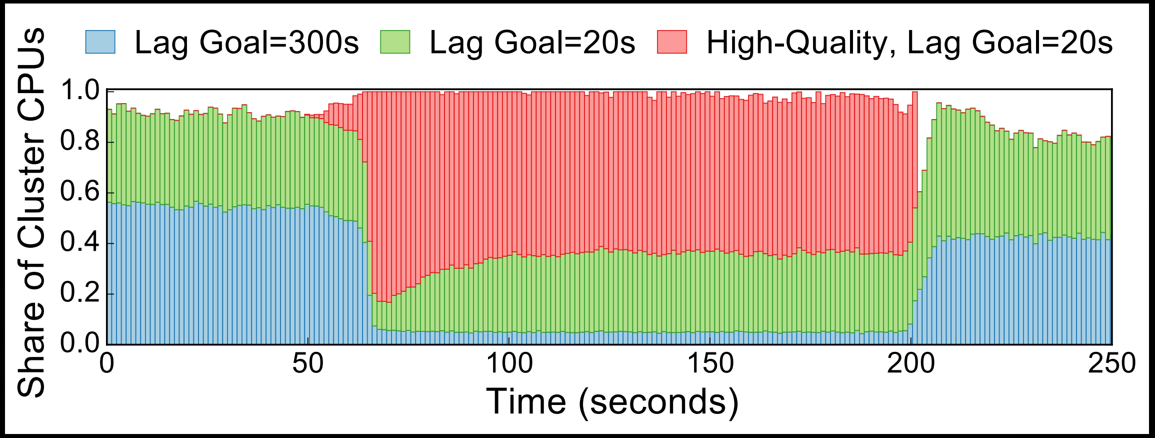


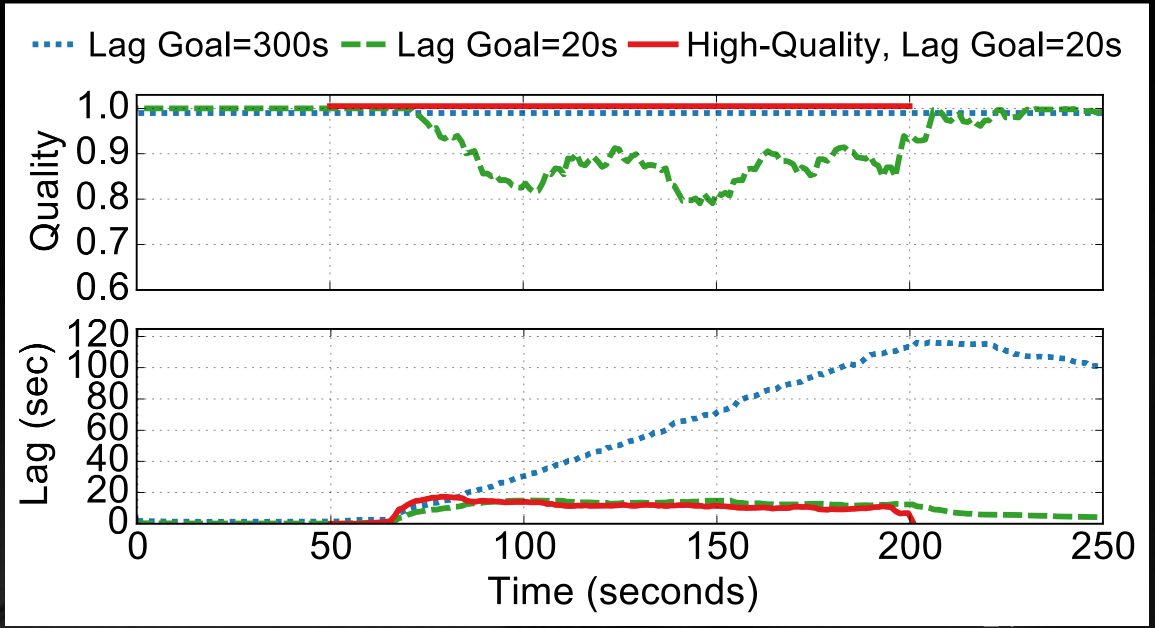
Resource allocation during burst of queries

- Start with 300 queries:
  ① Lag Goal=300s, low-quality ~60%
  ② Lag Goal=20s, low-quality ~40%

- Burst of 150 seconds (50 – 200):
  ③ 200 LPR queries (AMBER Alert)
  High-Quality, Lag Goal=20s

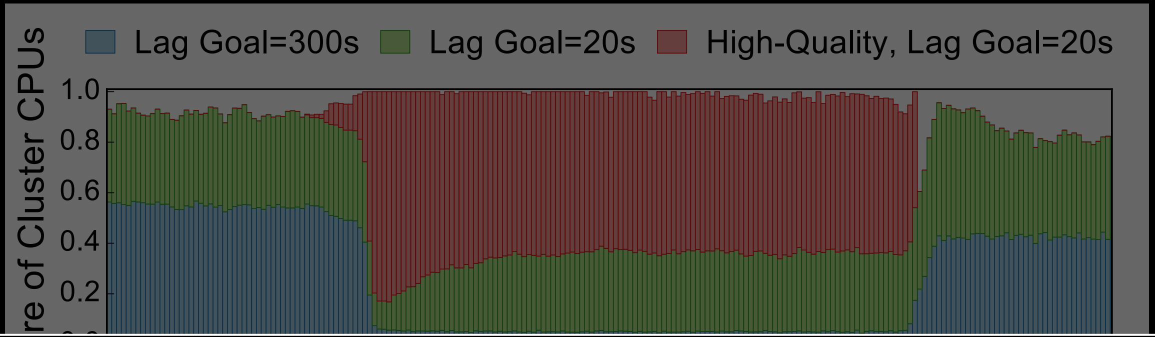
- VideoStorm scheduler:
  ③ dominate resource allocation
  significantly delay ①
  run ② with lower quality
  All meet quality and lag goals





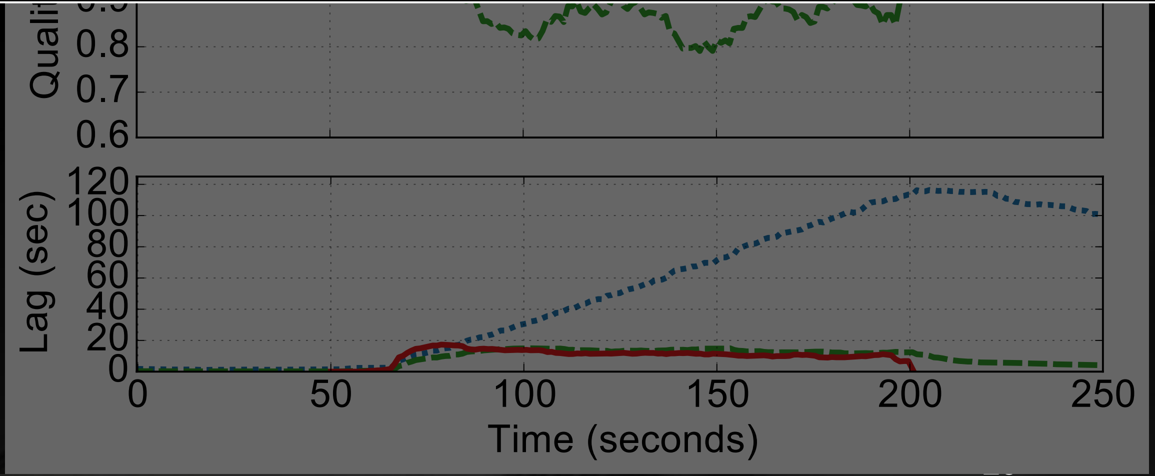
Resource allocation during burst of queries

- Start with 300 queries:
  ① Lag Goal=300s, low-quality ~60%
  ② Lag Goal=20s, low-quality ~40%



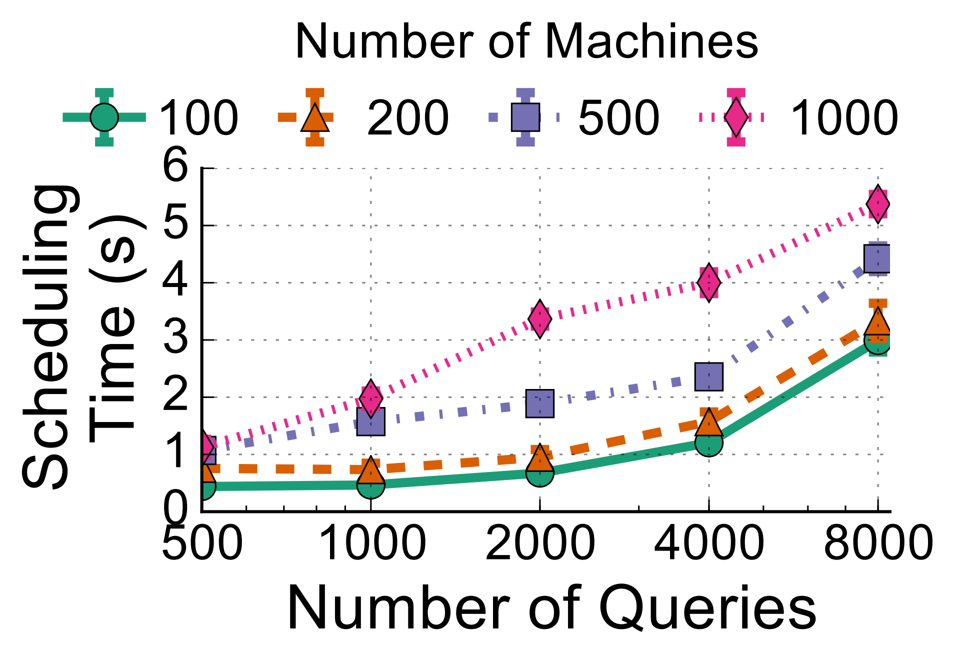
- Compare to a fair scheduler with varying burst duration:
  - Quality improvement: up to 80%
  - Lag reduction: up to 7x

- VideoStorm scheduler:
  significantly delay ①
  run ② with lower quality
  ③ dominate resource allocation
  All meet quality and lag goals



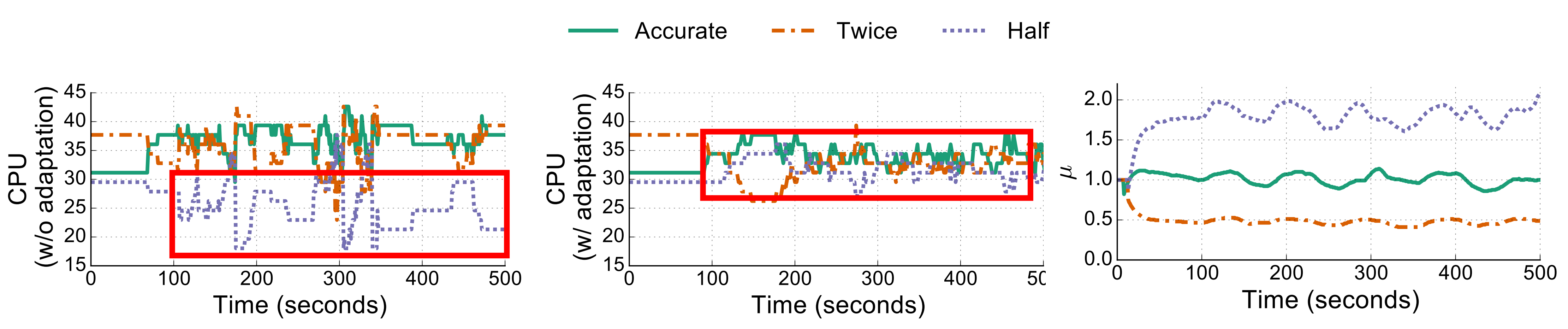
VideoStorm Scalability

- Frequently reschedule and reconfigure in reaction to changes of queries
- Even with thousands of queries, VideoStorm makes rescheduling decisions in just a few seconds



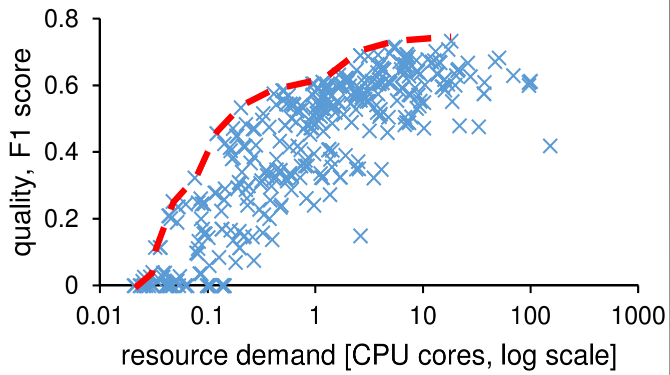
VideoStorm: account for errors in query profiles

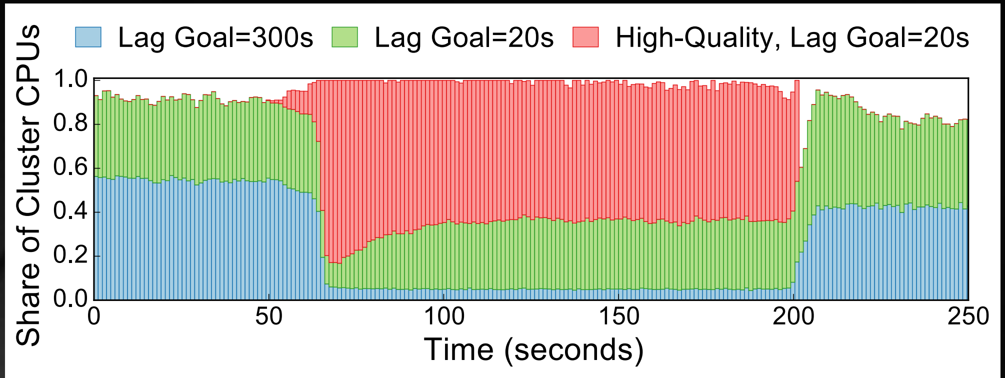
- Errors in profile on resource demands
  - Over/under allocate resources → miss quality and lag goals!
- Example: 3 copies of same query, *should* get same allocation
  - Profiled resource synthetically doubled, halved and unchanged
- VideoStorm keeps track of mis-estimation factor μ – multiplicative error between the profiled demand and actual usage



Conclusion

- VideoStorm is a video analytics system that scales to processing thousands of video streams in large clusters





- Offline profiler: efficiently estimates resource-quality profiles
- Online scheduler: optimizes jointly for the quality and lag of queries

- VideoStorm is currently deployed in Bellevue Traffic Department, and soon will be deployed in more cities