Adapting Swarm Application

A Systematic and Quantitative Approach

Ben Zhang

December 6, 2019

TerraSwarm Research Center

https://github.com/nebgnahz/dissertation-talk

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The Swarm at the Edge of the Cloud

J. Rabaey, ASPDAC'08

The Swarm at the Edge of the Cloud

J. Rabaey, ASPDAC'08

Swarm, or

- Internet of Things (IoT)
- Internet of Everything (IoE)
- Industry 4.0
- The Industrial Internet
- TSensors (Trillion Sensors)
- Machine to Machine (M2M)
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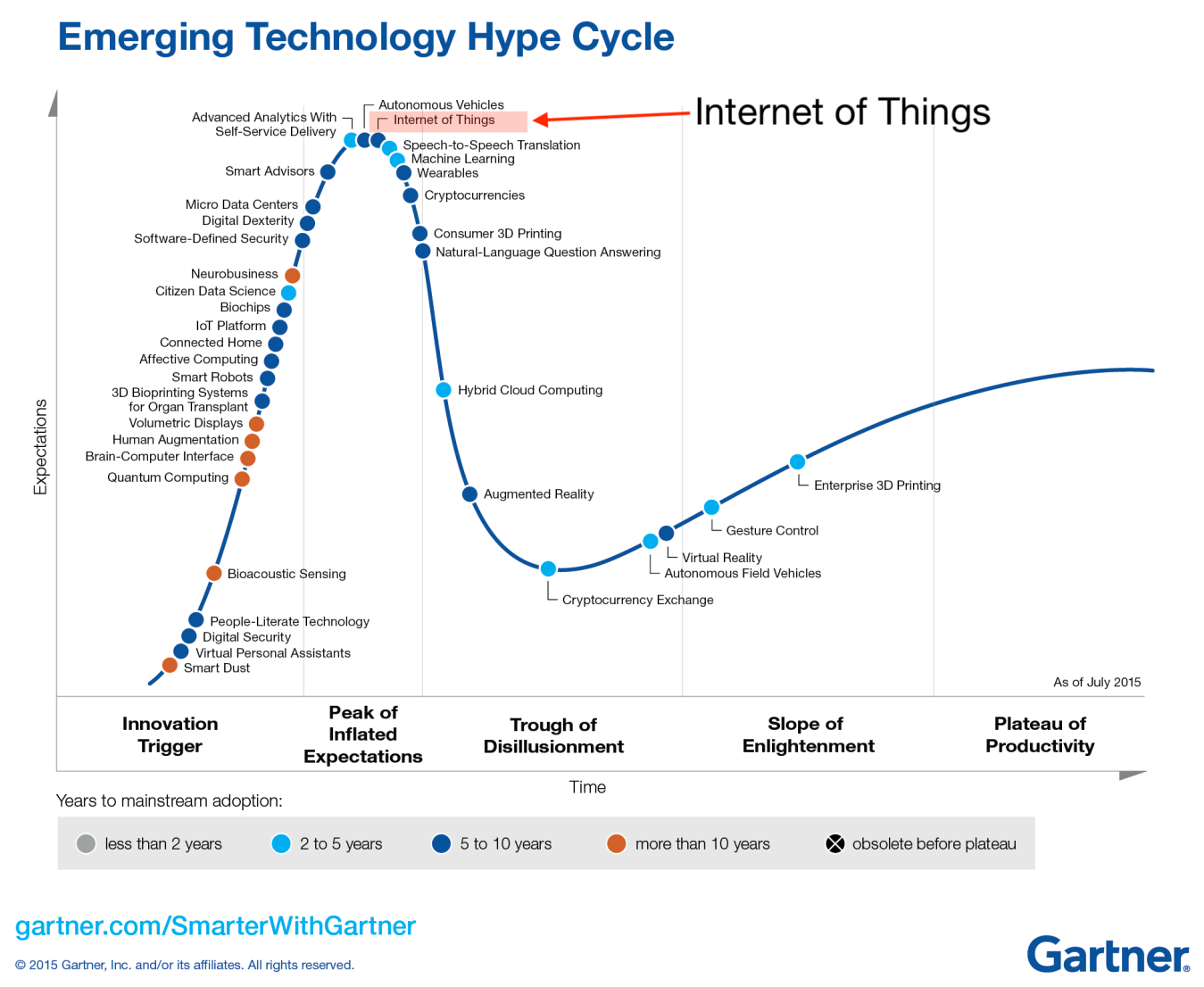
SWARM Lab UC BERKELEY

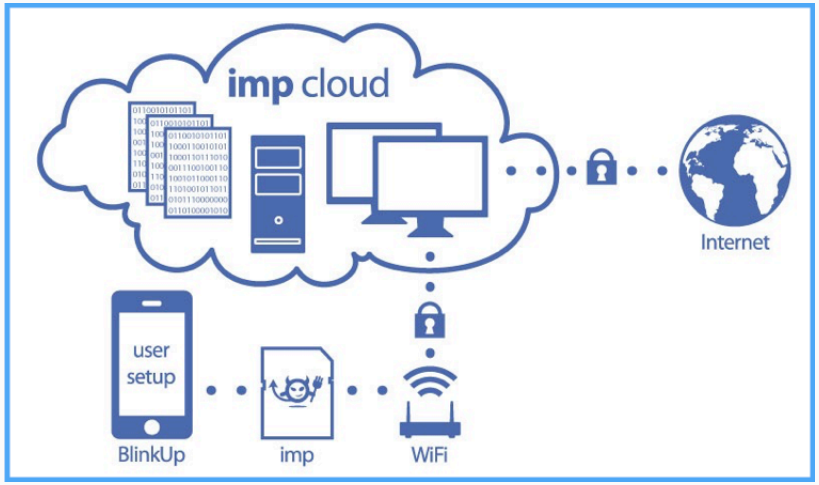
TerraSwarm

UC BERKELEY SWARMLAB 2.0

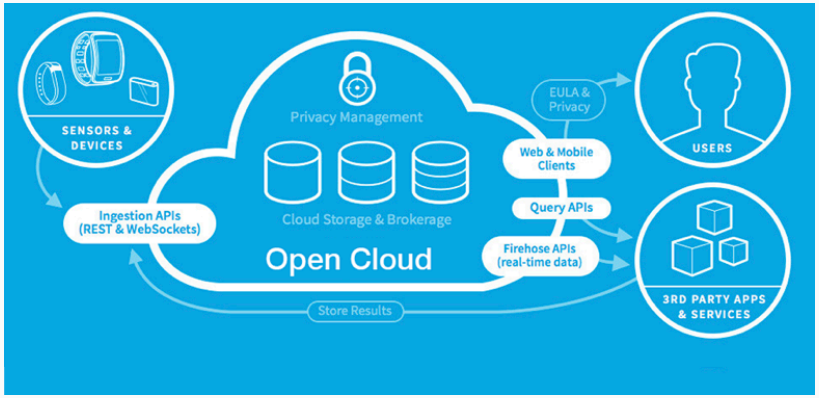
Gartner Hype Cycle (2015)



A Cloud-centric Approach



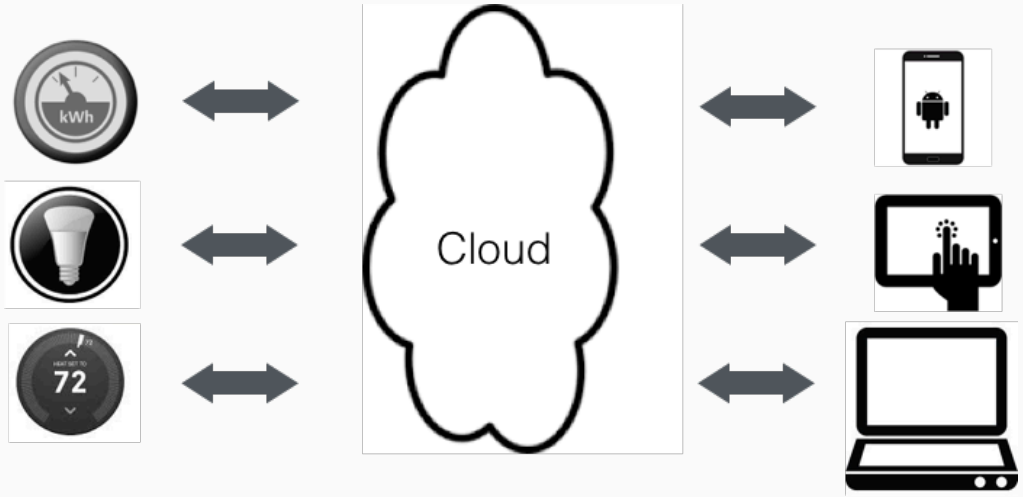
(a) Electric Imp



(b) Samsung SAMI

(c) Ninja Sphere

“The Cloud”: Model vs. Reality



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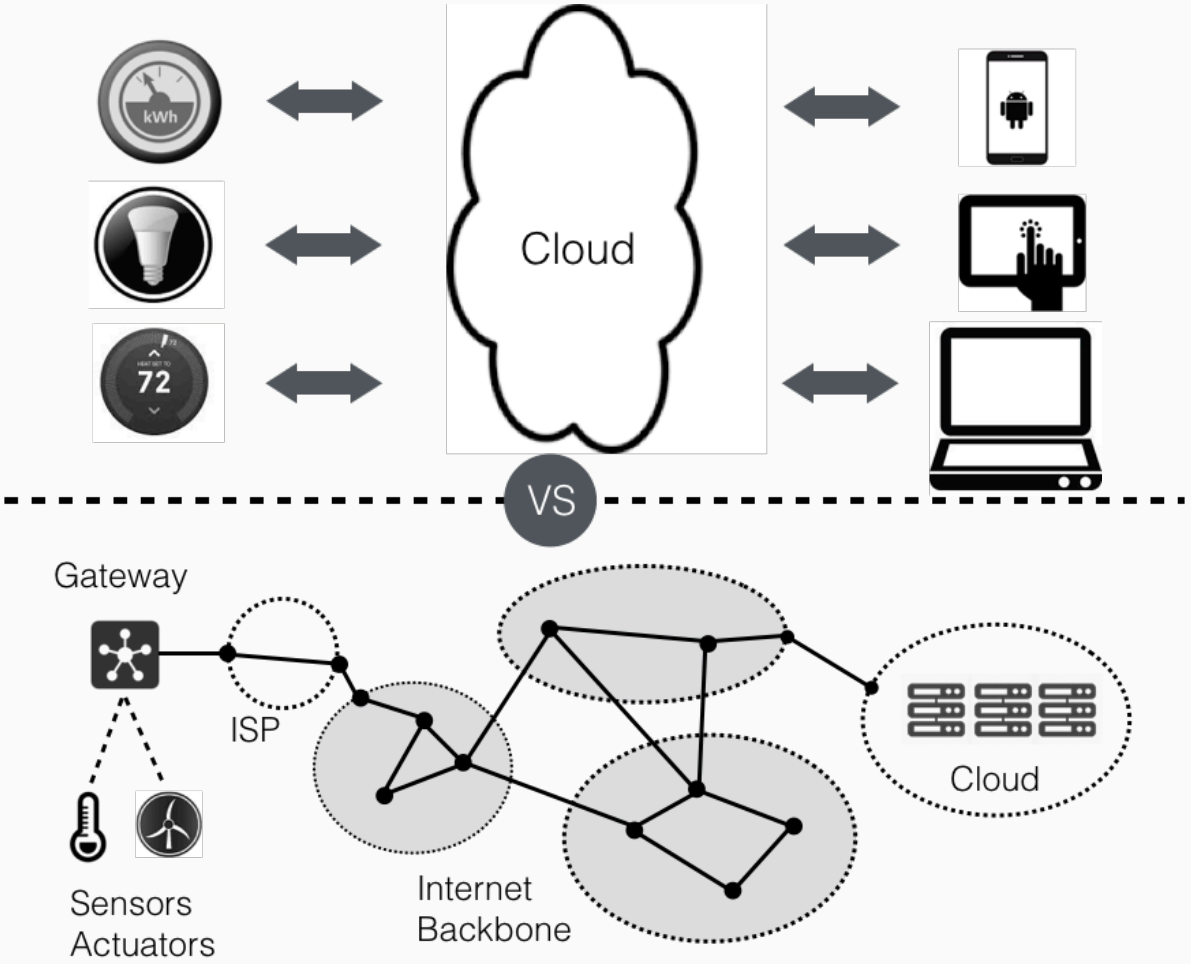

The Cloud is Not Enough

	Web/IT	Swarm/IoT
Privacy & Security	Open for access	Sensitive data
Scalability	Power law	Billion devices
Interaction Model	Human	Machine
Latency	Variable	Bounded
Bandwidth	Downstream	Upstream
Availability (QoS)	No guarantee	Requirement
Durability Management	Cloud controls	Users control

Pitfalls with Today's Approach to IoT [Zhang et al., 2015]

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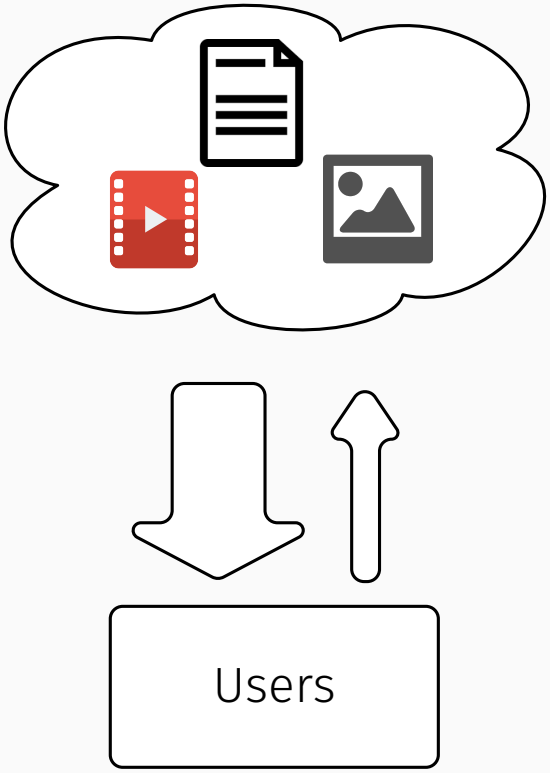
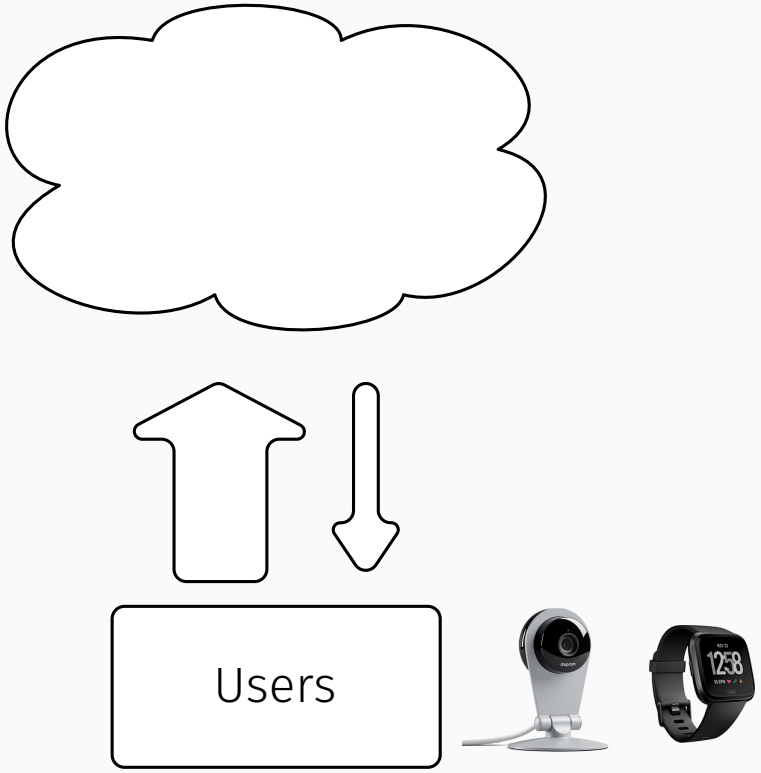
Bandwidth: Downstream vs. Upstream



Web/IT



Swarm/IoT

Network Resource Adaptation

Limited Network Resource

Demand
Huge Data Volume at the Edge

Resource
Insufficient WAN Bandwidth

Limited Network Resource

Demand	Resource
Huge Data Volume at the Edge	Insufficient WAN Bandwidth

- Video surveillance, 3 mbps per camera [Amerasinghe, 2009]
- Electrical grid monitoring, 1.4 million data points per second [Andersen and Culler, 2016]
- Machine logs, 25 TB daily at Facebook (2009)

Limited Network Resource

Demand	Resource
Huge Data Volume at the Edge	Insufficient WAN Bandwidth

. . . Dropcam, a WiFi video-streaming camera and associated cloud backend service for storing and watching the resulting video. Dropcam has the fewest clients (2,940) . . . . Yet, each client uses roughly 2.8 GB a week and uploads nearly 19 times more than they download, implying that Dropcam users do not often watch what they record.

Large-scale Measurements of Wireless Network Behavior
[Biswas et al., 2015]

Limited Network Resource

Demand
Huge Data Volume at the Edge

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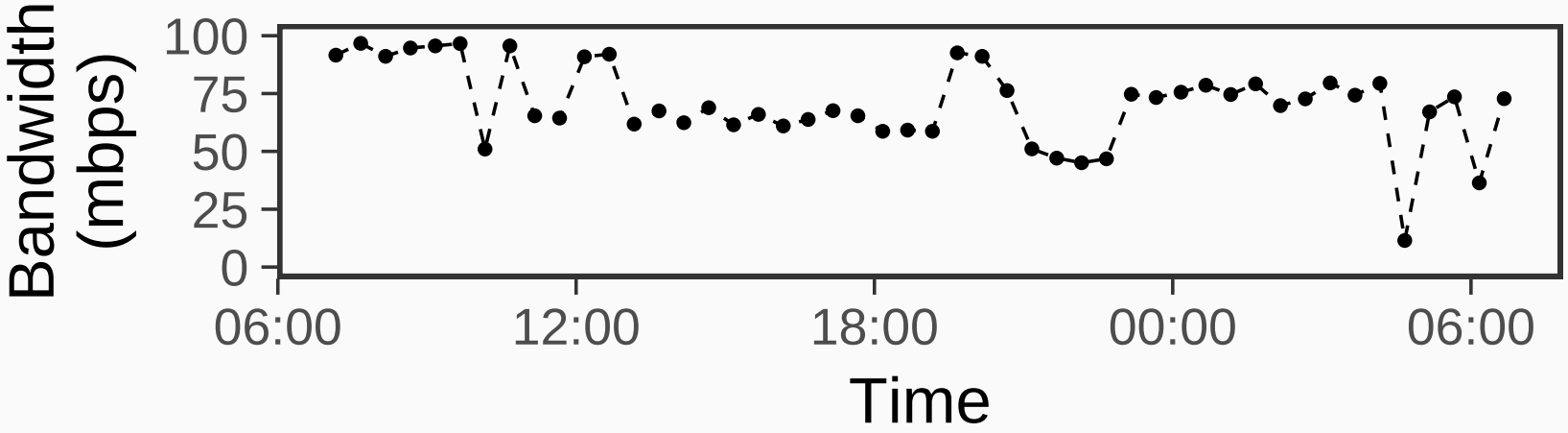

Bandwidth variations throughout the day between Amazon EC2 sites. Similar scarcity and variation for wireless networks, broadband access networks and cellular networks (backup slides).

Limited Network Resource

Demand	Resource
Huge Data Volume at the Edge	Insufficient WAN Bandwidth

What about edge processing? (I will cover in the second half of this talk).

But communication is not avoidable.

- Large performance gap between the cloud and the edge (GPU/TPU/ASIC).
- Aggregation is sometimes necessary in applications.
- Last-hop wireless may become the bottleneck.

Fidelity vs. Freshness

When the network resource is not sufficient:

- TCP ensures data delivery, but hurts latency
- UDP sends as fast as possible, uncontrolled packet loss

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Fidelity vs. Freshness

When the network resource is not sufficient:

- TCP ensures data delivery, but hurts latency
- UDP sends as fast as possible, uncontrolled packet loss
- Manual policies (developer heuristics) are sub-optimal
  - JetStream [Rabkin et al., 2014] uses manual policy
  - "if bandwidth is insufficient, switch to sending images at 75% fidelity, then 50% if still not enough"

Fidelity vs. Freshness

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Fidelity vs. Freshness

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- Manual policies (developer heuristics) are sub-optimal
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  - Video streaming often aims at Quality of Experience (limited degradation dimension, e.g. maintain 25FPS)
  - For object detection, resolution matters more than FPS

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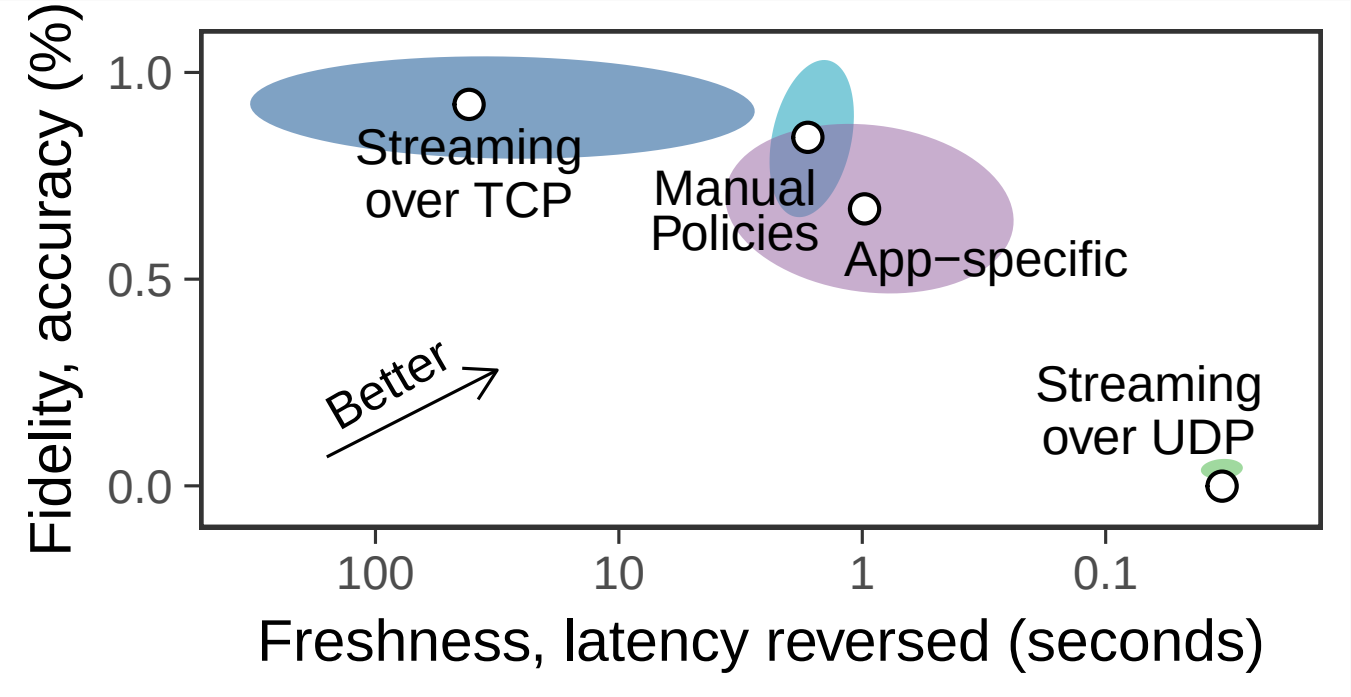

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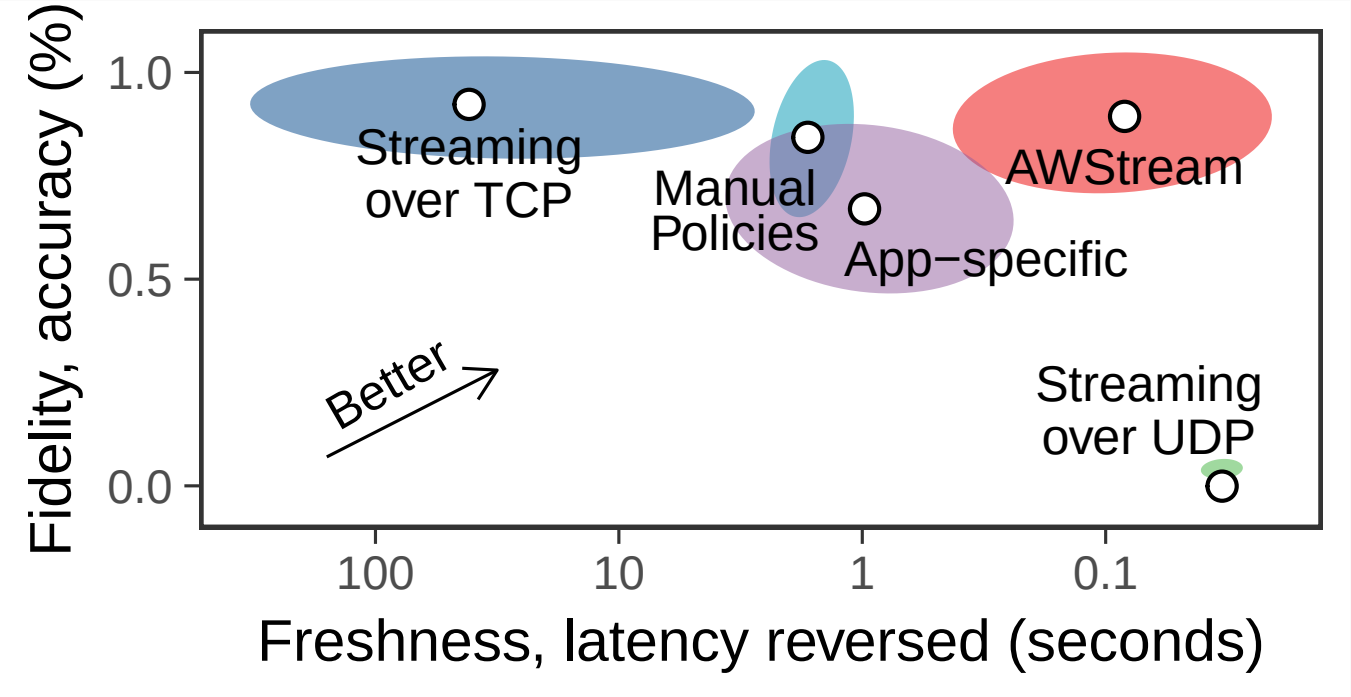
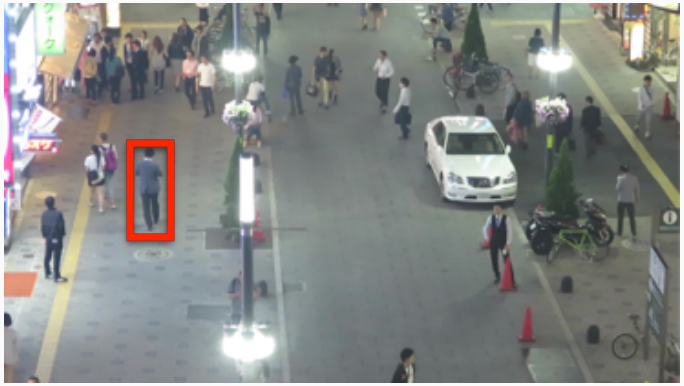


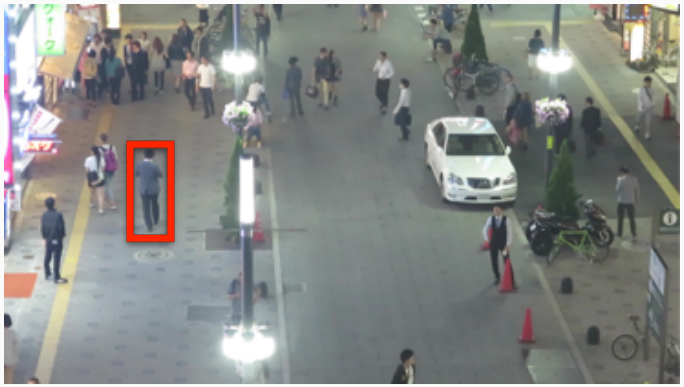
Application-specific Optimizations Don't Generalize



t=0s, small target in far-field views

t=1s, small difference

Application-specific Optimizations Don't Generalize



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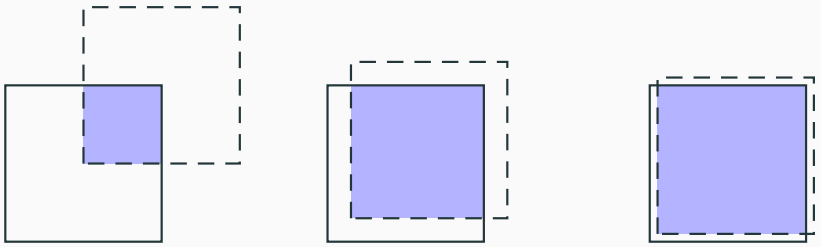
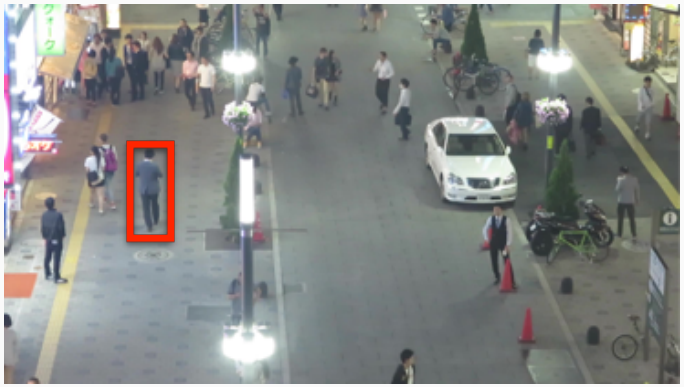
Positive if intersection over union (IOU) larger than 0.5.

$$\text{IOU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$



(a) IOU=0.14 (b) IOU=0.57 (c) IOU=0.82

Application-specific Optimizations Don't Generalize



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F1 score is the harmonic mean of precision and recall, ranging from 0 to 1:

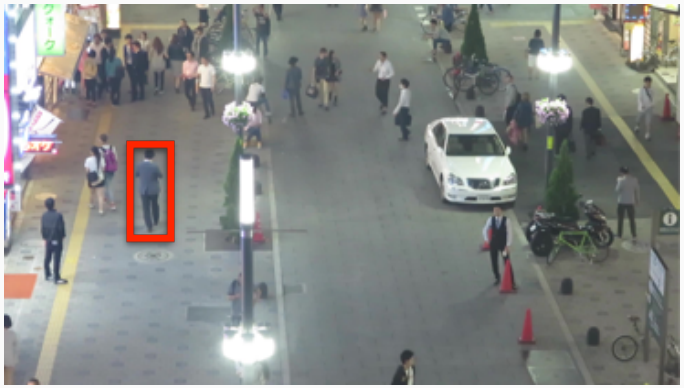
	P	N
Y	True Positive	False Positive
N	False Negative	True Negative

$$\text{Precision} = \frac{\text{true positive}}{\text{all positive}}$$

$$\text{Recall} = \frac{\text{true positive}}{\text{all detection}}$$

$$\text{F1} = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$$

Application-specific Optimizations Don't Generalize



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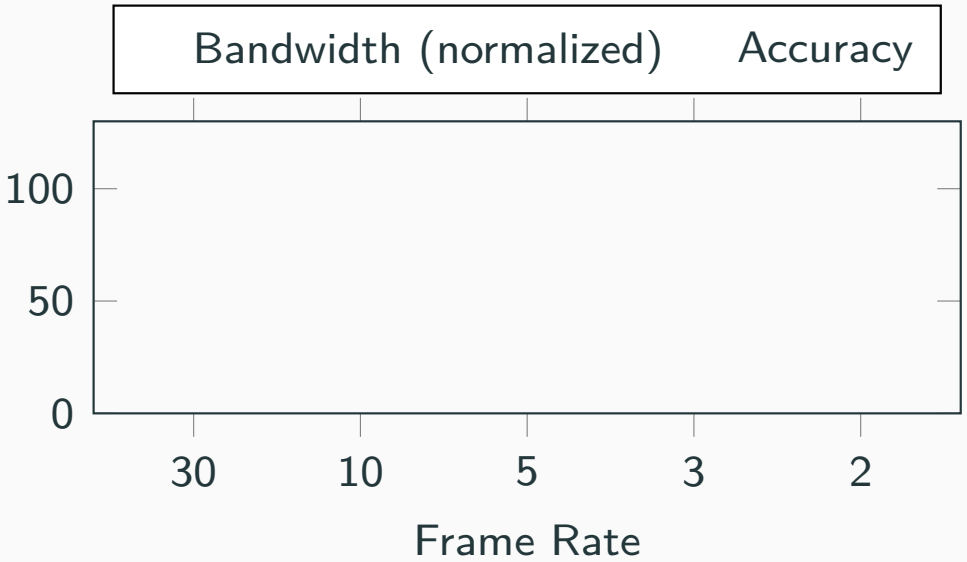

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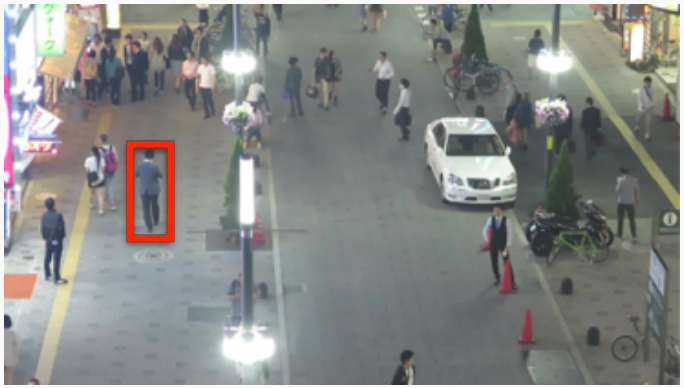

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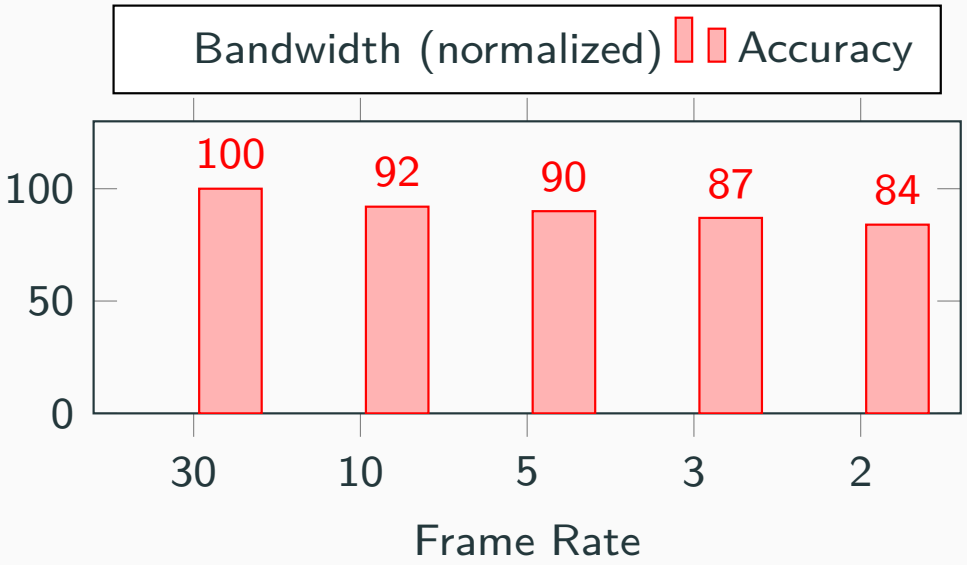

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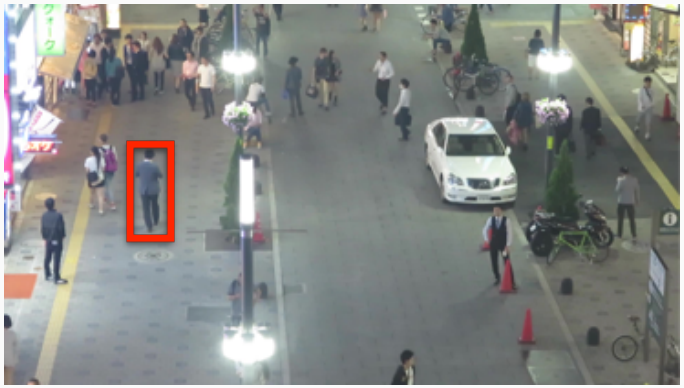

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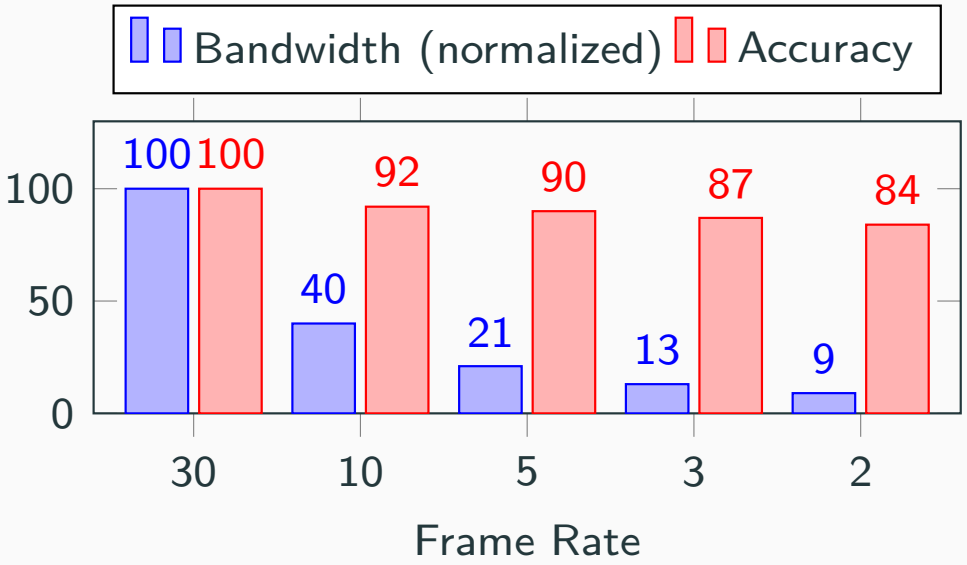

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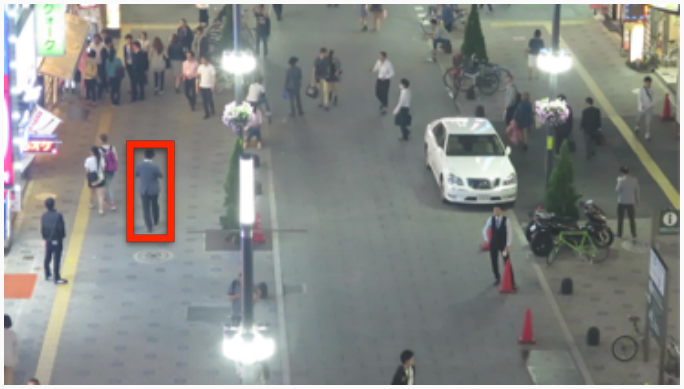

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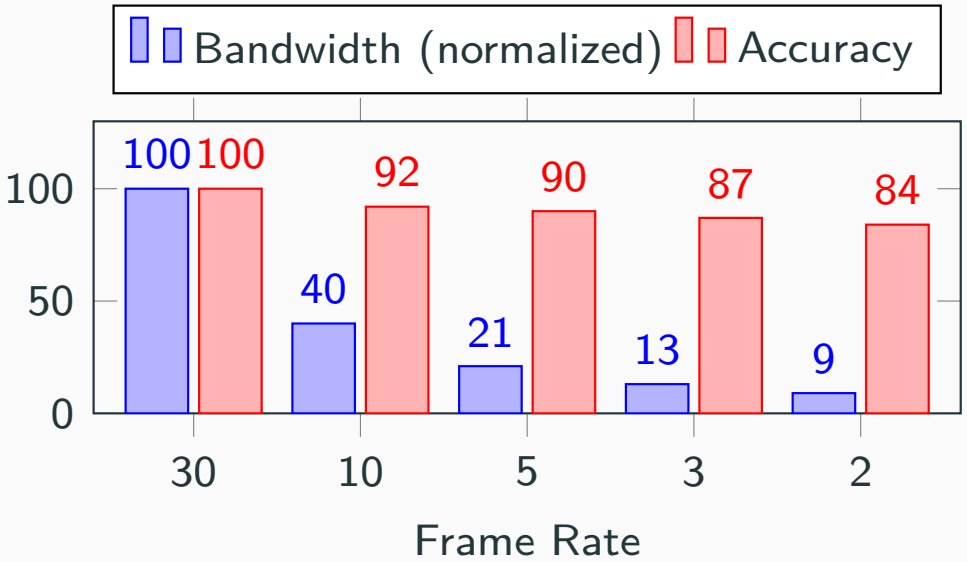

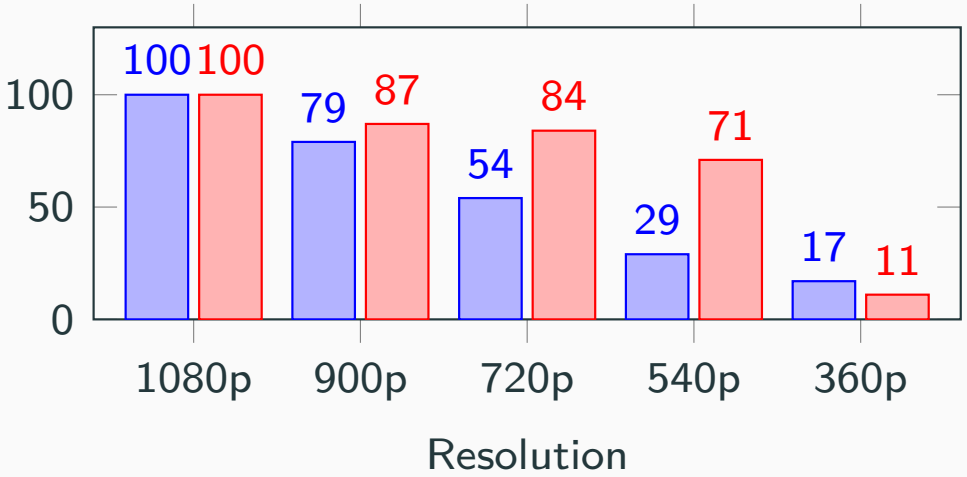

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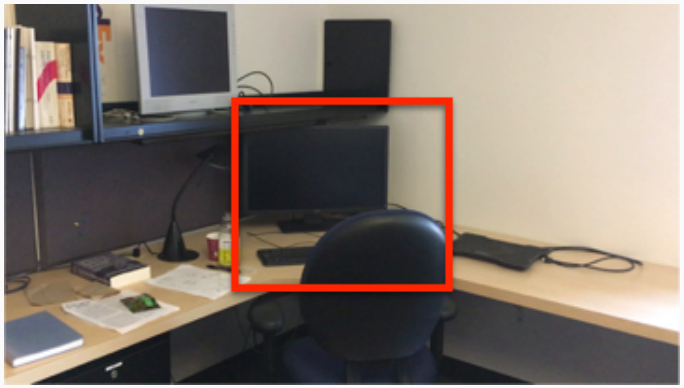
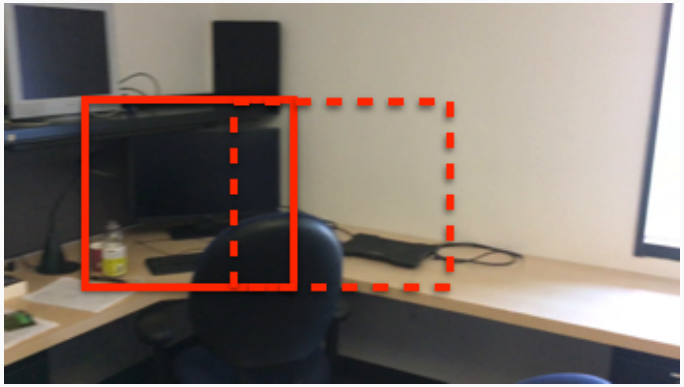
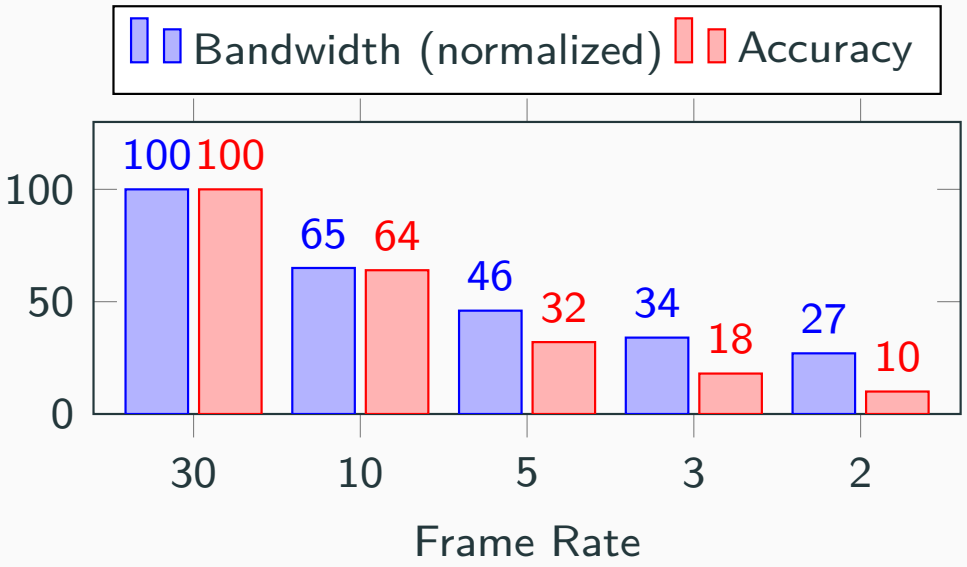
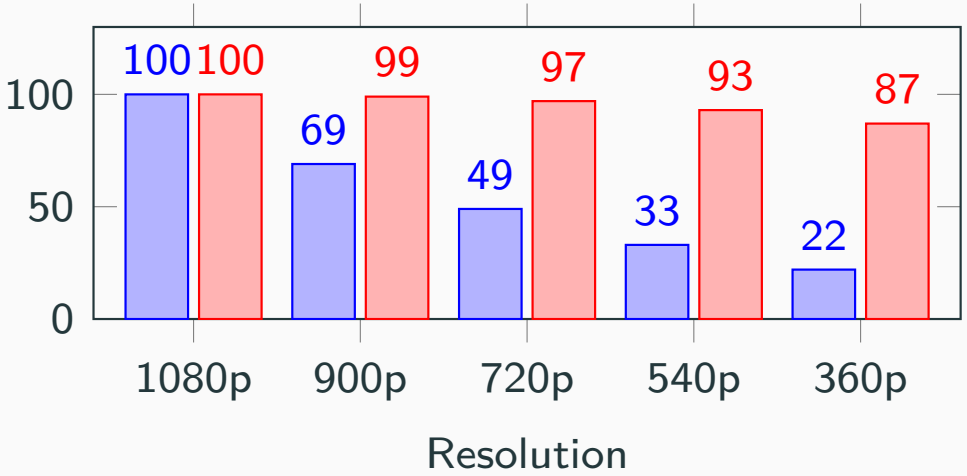


t=0s, nearby and large targets



t=1s, large difference





Making Adaptation Practical is Challenging

Goal

Minimize bandwidth while maximizing application accuracy

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3. The adaptation happens at the runtime.

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   - Profiling: automatically learn Pareto-optimal strategy with multi-dimensional exploration.
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   - Profiling: automatically learn Pareto-optimal strategy with multi-dimensional exploration.
3. The adaptation happens at the runtime.
   - Engineering an adaptation system to balance latency and accuracy.

Making Adaptation Practical is Challenging

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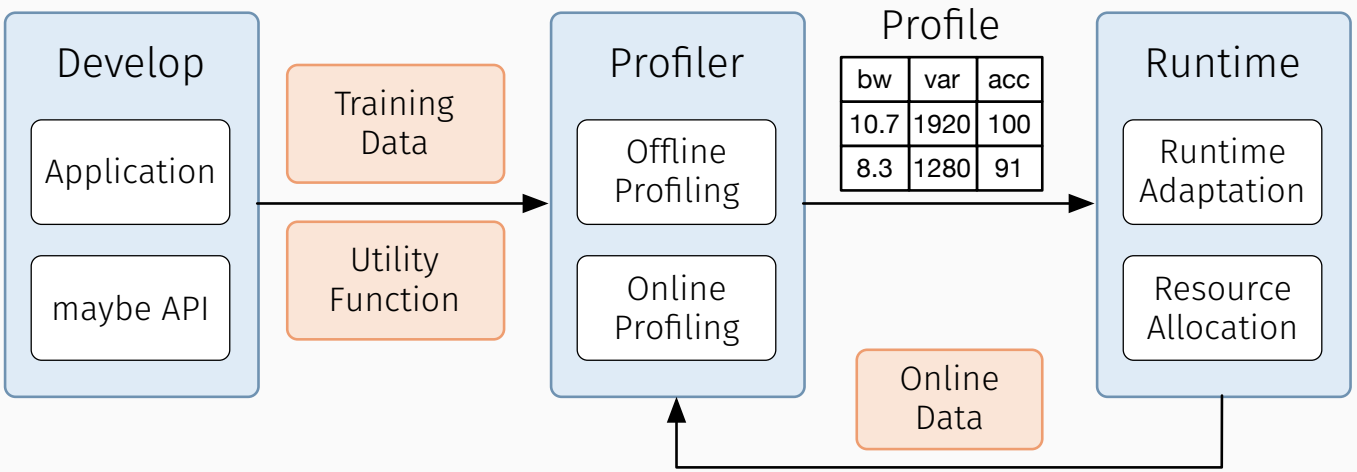
Minimize bandwidth while maximizing application accuracy



(1) Stream Processing APIs

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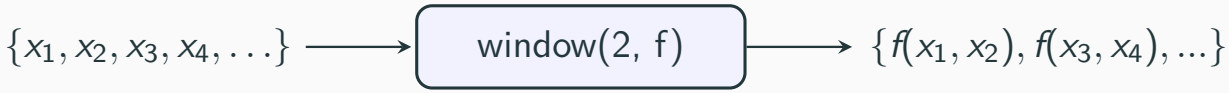

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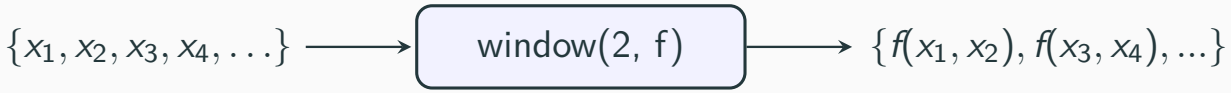
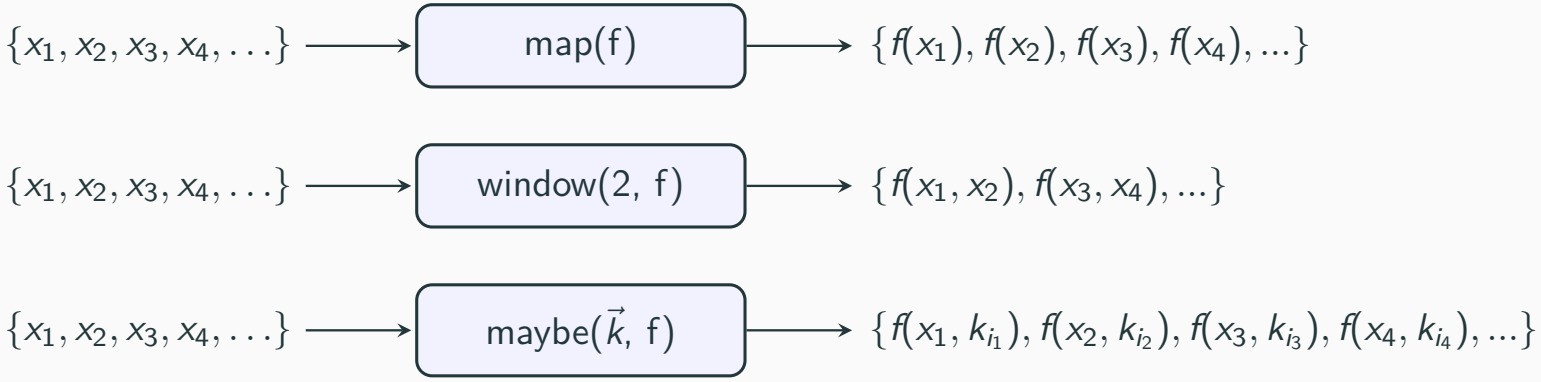


Normal	*map* (f: I ⇒ O)	Stream<I> ⇒ Stream<O>
	skip (i: Integer)	Stream<I> ⇒ Stream<I>
	window (count: Integer, f: Vec<I> ⇒ O)	Stream<I> ⇒ Stream<O>
	...	...

(1) Stream Processing APIs



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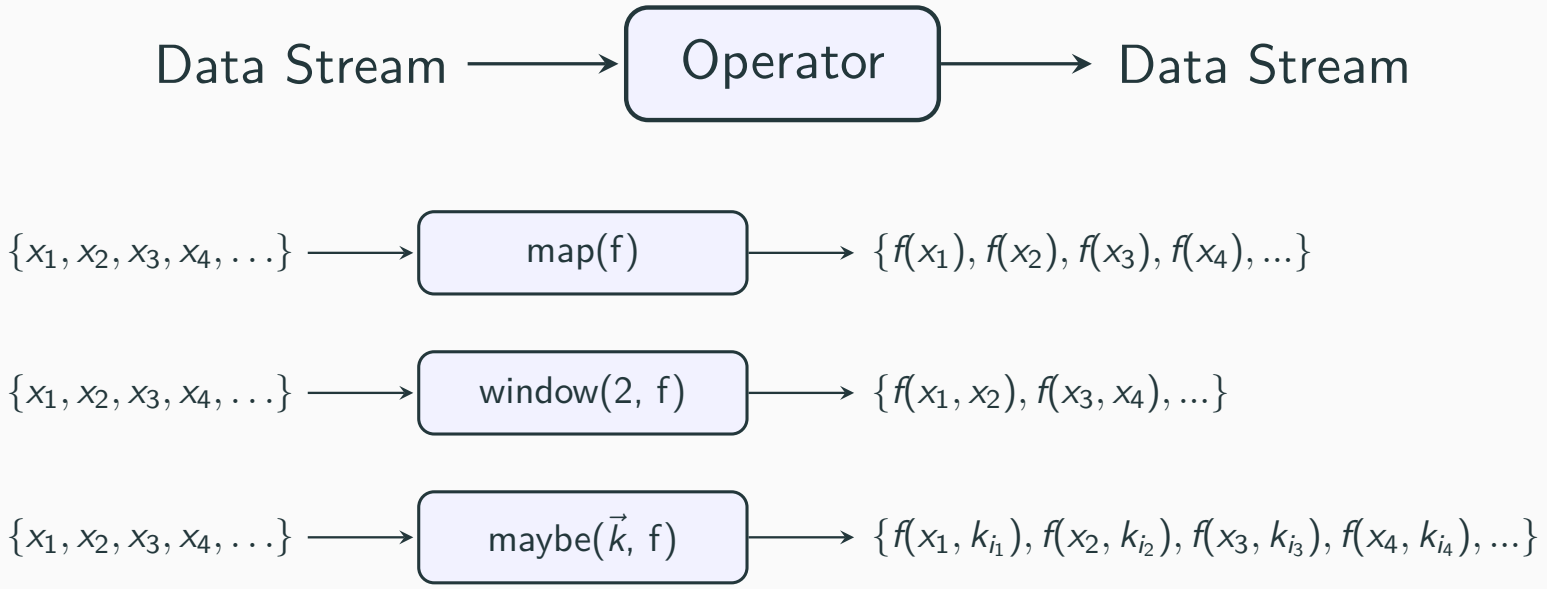

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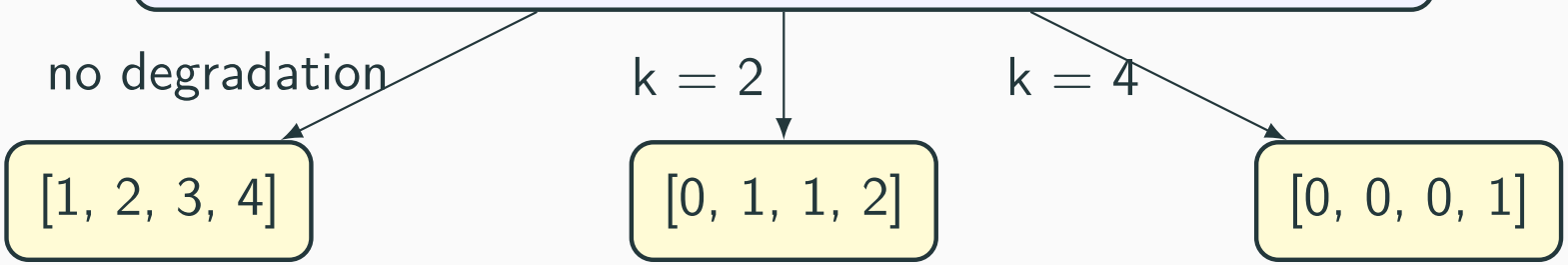
	window (count: Integer, f: Vec<I> ⇒ O)	Stream<I> ⇒ Stream<O>
	...	...
Adaptation	*maybe* (knobs: Vec<T>, f: (T, I) ⇒ I)	Stream<I> ⇒ Stream<I>
	maybe_skip (knobs: Vec<Integer>)	Stream<I> ⇒ Stream<I>
	maybe_head (knobs: Vec<Integer>)	Stream<Vec<I>> ⇒ Stream<Vec<I>>
	...	...

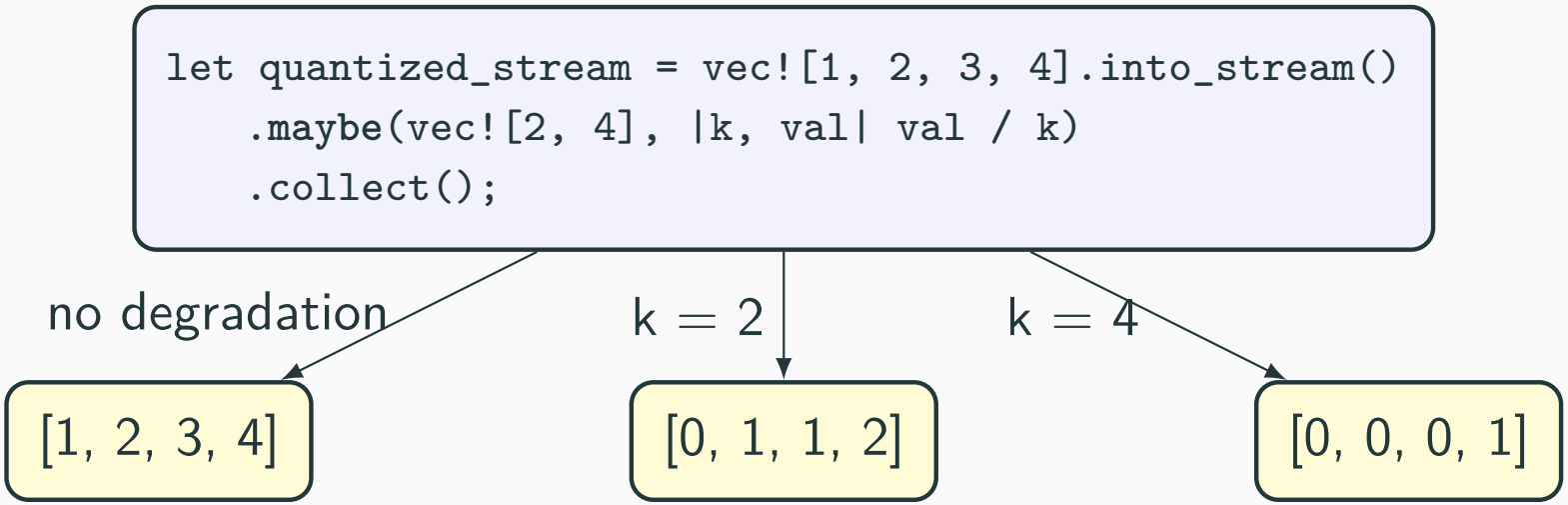
maybe(knobs: Vec<T>, f: (T, I) => I)

```
let quantized_stream = vec![1, 2, 3, 4].into_stream()
    .maybe(vec![2, 4], |k, val| val / k)
    .collect();
```



Example code in Rust, simplified for presentation.

maybe(knobs: Vec<T>, f: (T, I) => I)



We rewrite the video streaming application as follows,

```
let app = Camera::new((1920, 1080), 30)
    .maybe_downsample(vec![(1600, 900), (1280, 720)])
    .maybe_skip(vec![2, 5])
    .map(|frame| pedestrian_detect(frame))
    .compose();
```

Example code in Rust, simplified for presentation.

(2) Profiling

```
let app = Camera::new((1920, 1080), 30)
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Training Data

(2) Profiling

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Training Data

Accuracy Function

(2) Profiling

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    .compose();
```
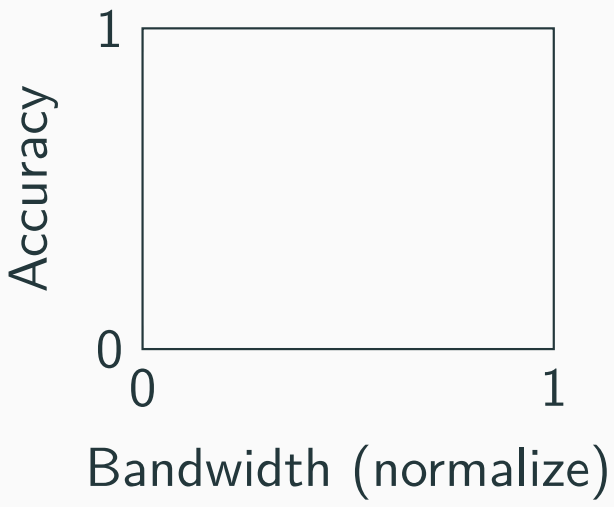

Training Data

Accuracy Function

downsample	skip	bandwidth	accuracy
(1920, 1080)	0	10.7	1.0
(1600, 900)	0	8.3	0.88
(1280, 720)	0	6.3	0.87
(1920, 1080)	2	9.3	0.90
...	...	...	...

Profile: Pareto-optimal Strategy



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k_i	the i-th degradation knob
$c = [k_1, k_2, \ldots k_n]$	one specific configuration
$\mathbb{C}$	the set of all configurations
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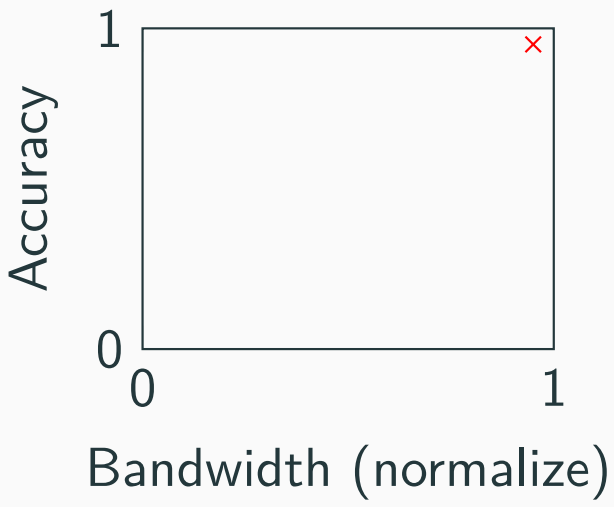

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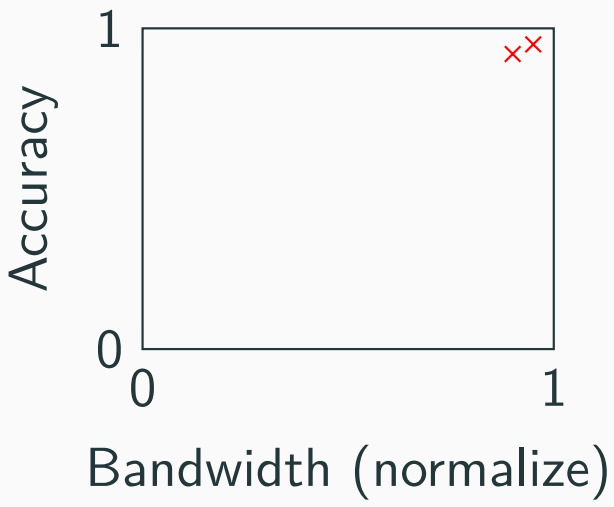

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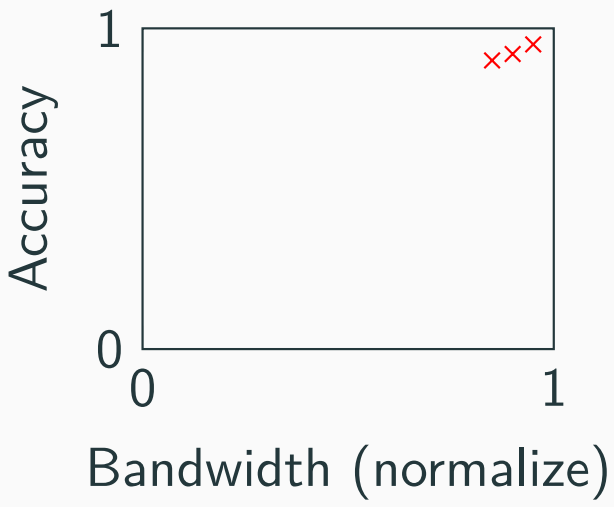

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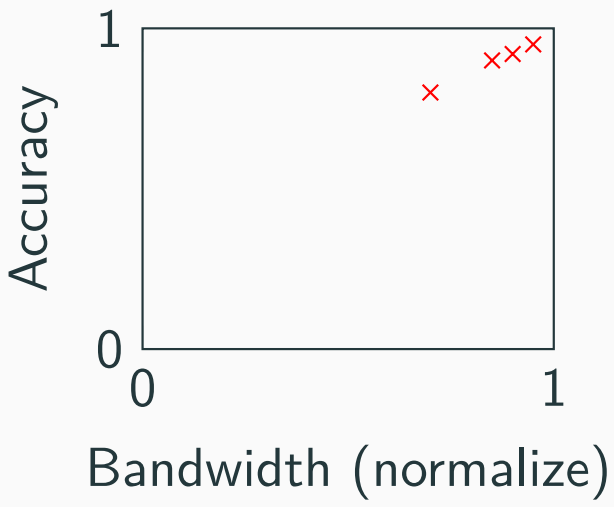

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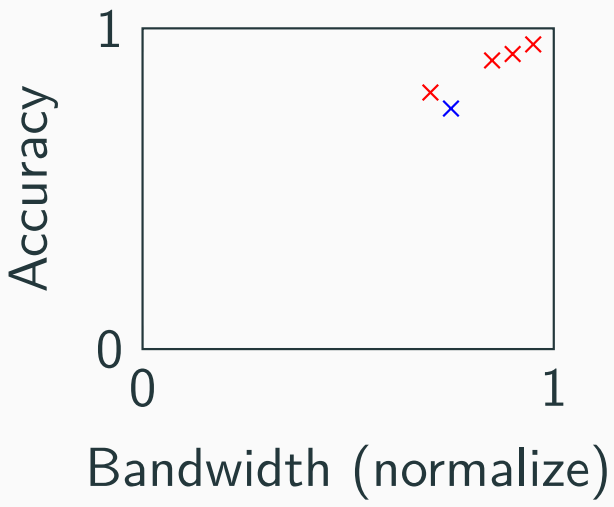

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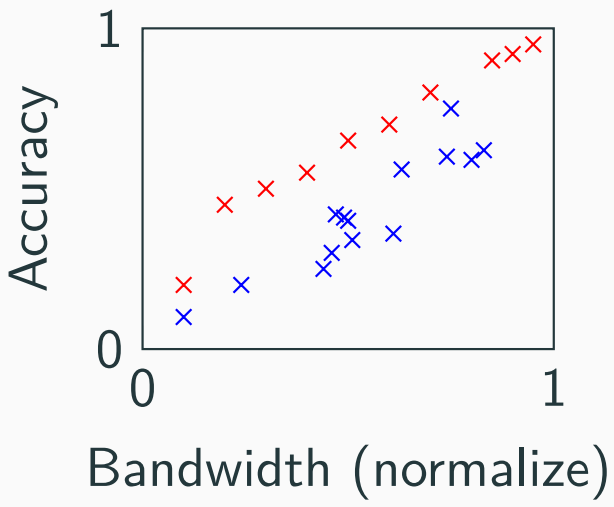

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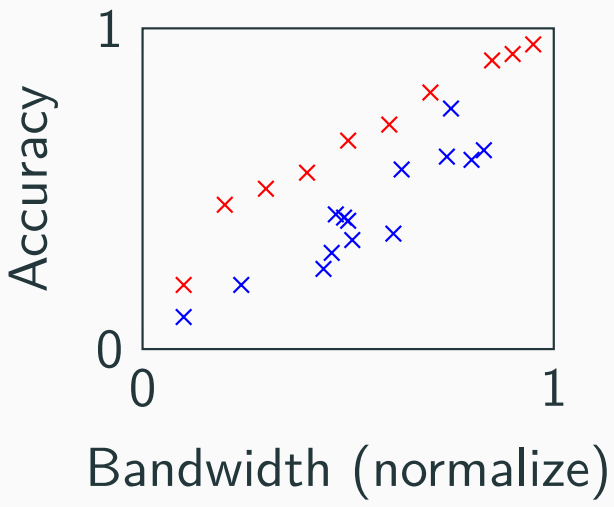

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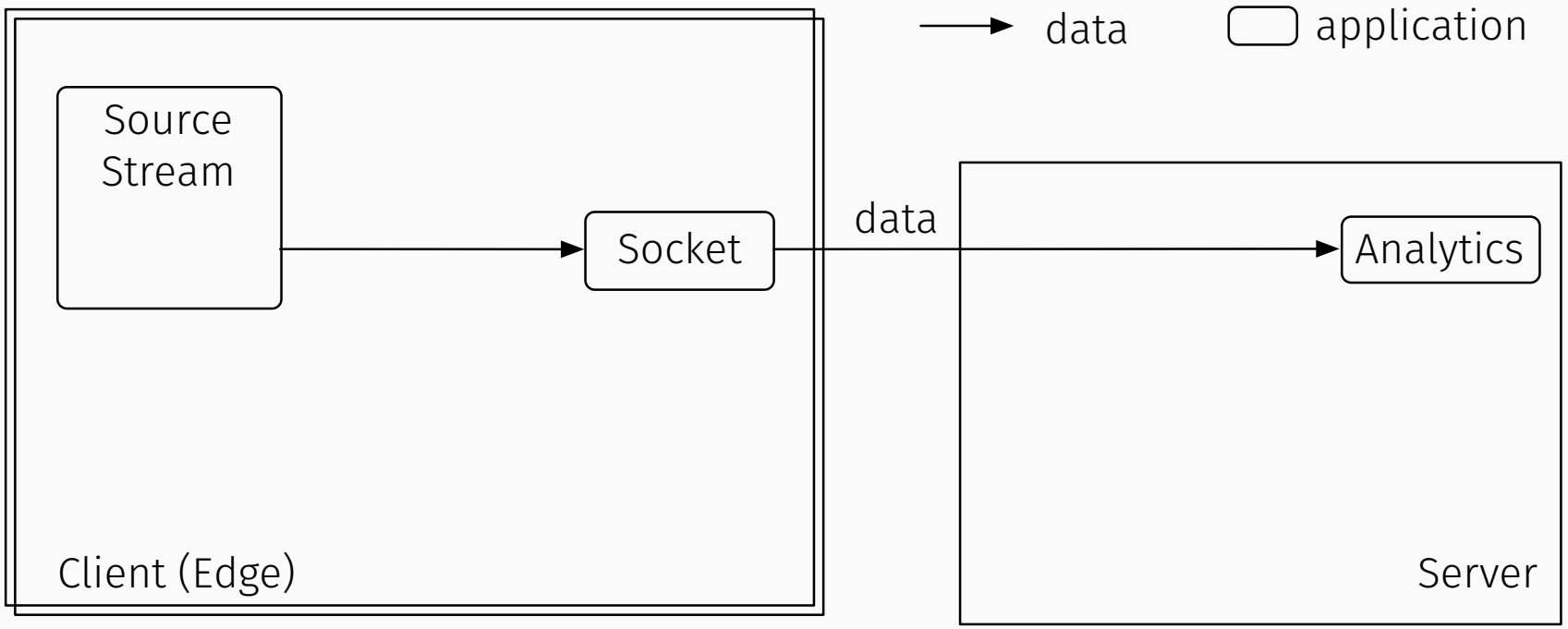
$$\mathbb{P} = \{c \in \mathbb{C} : \underbrace{\{c' \in \mathbb{C} : B(c') < B(c), A(c') > A(c)\}}_{\text{set of better configurations } c'} = \varnothing\}$$

See red markers in the figure.

(3) Runtime Adaptation



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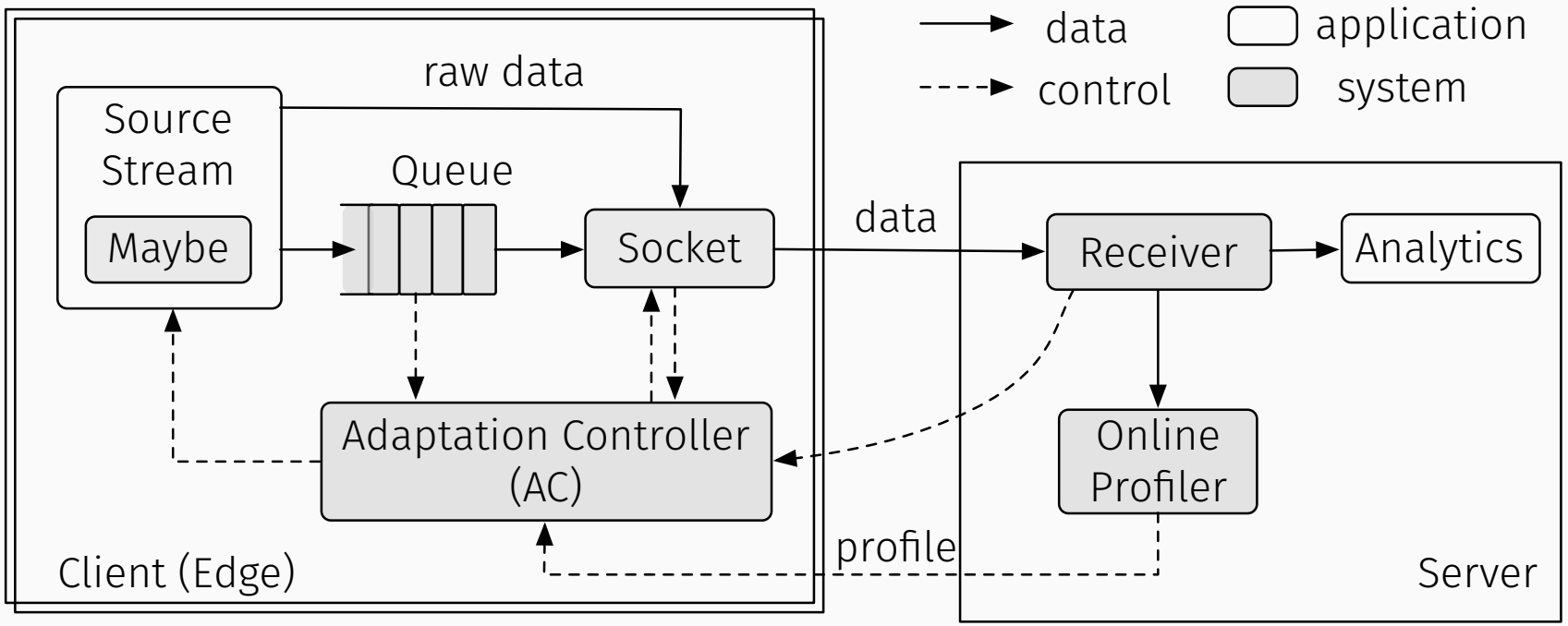

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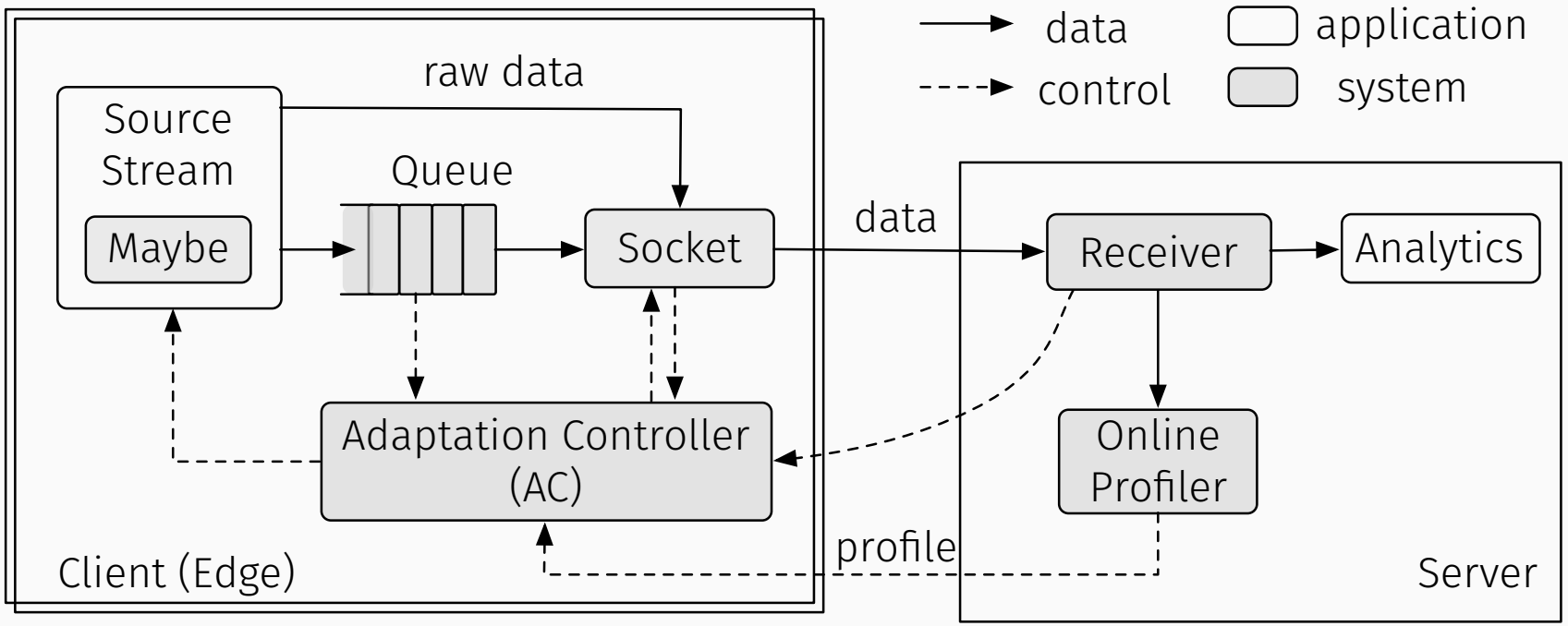
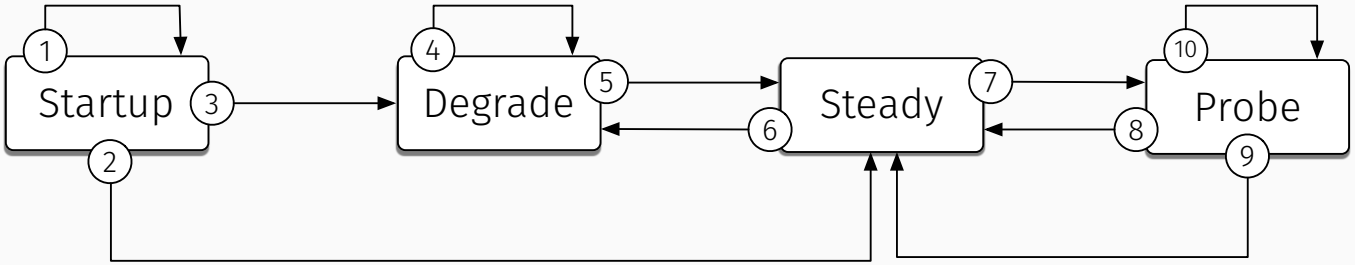
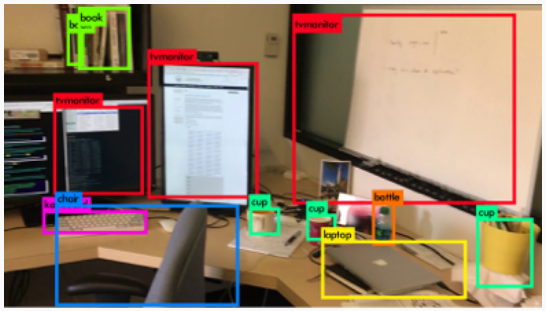


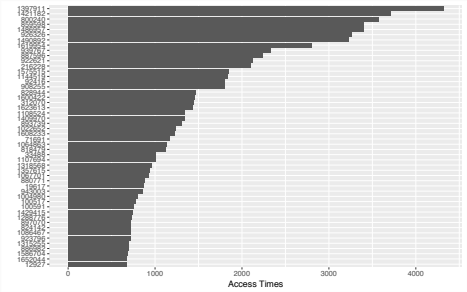


Adaptation Controller State Machine. We introduce `Probe` phase to conservatively change adaptation level. For details, please see the paper/thesis.

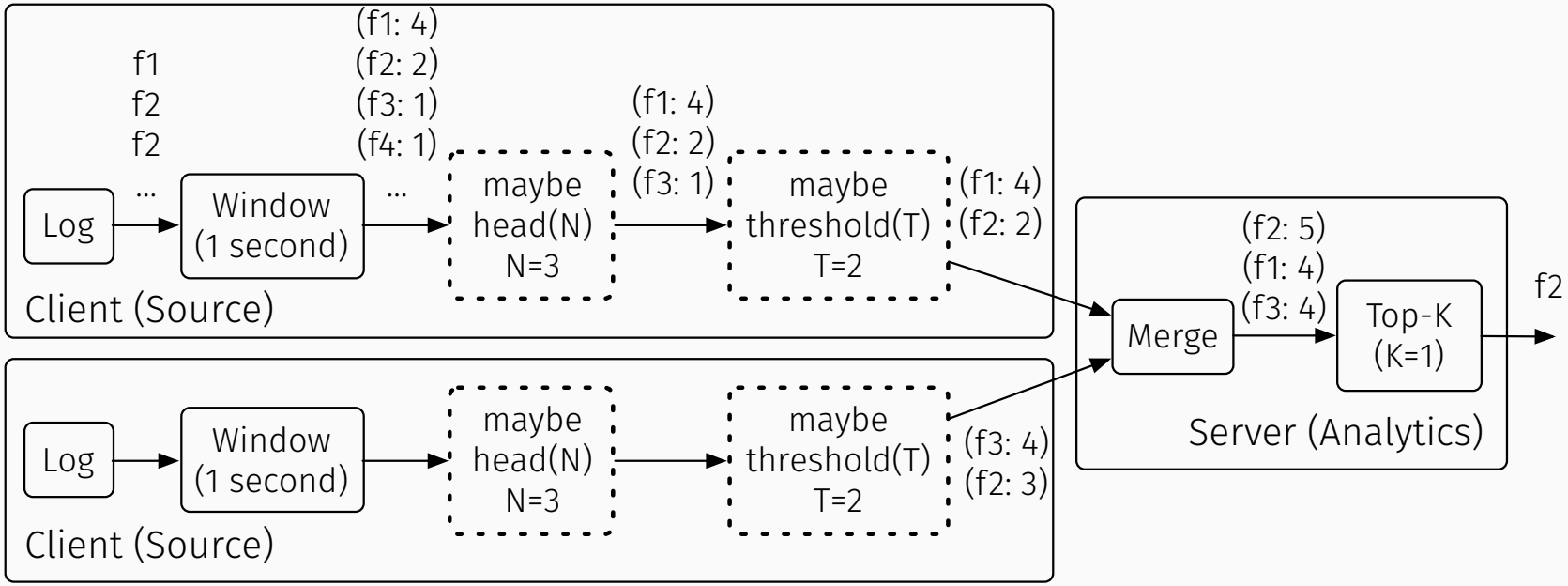
Applications

Application	Knobs	Accuracy	Dataset
Augmented Reality	resolution frame rate quantization	F1 score [Rijsbergen, 1979]	iPhone video clips training: office (24s) testing: home (246s)
Pedestrian Detection	resolution frame rate quantization	F1 score	MOT16 [Milan et al., 2016] training: MOT16-04 testing: MOT16-03
Log Analysis (Top-K, K=50)	head (N) threshold (T)	Kendall's τ [Abdi, 2007]	SEC.gov logs [DERA, 2016] training: 4 days testing: 16 days



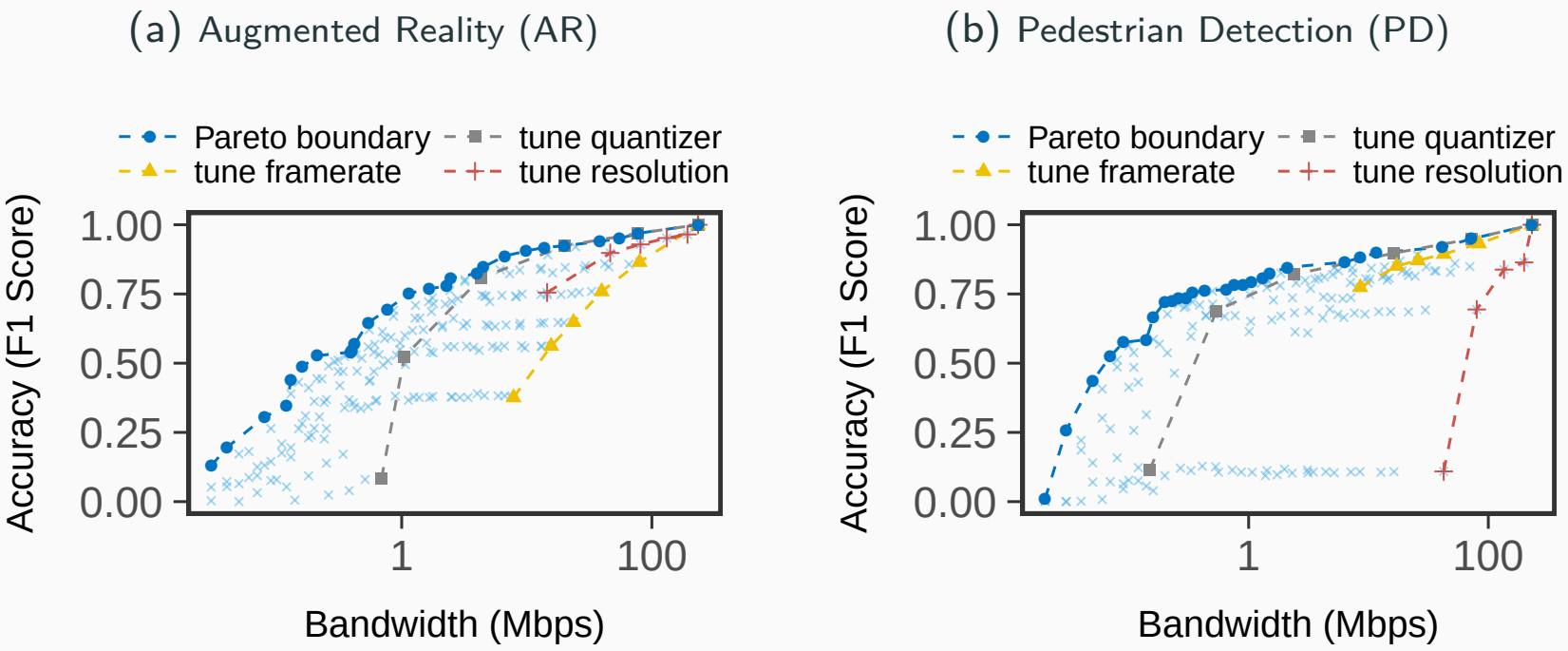


Top-K



A distributed Top-K application with two degradation operations: `head` and `threshold`. In this example, `f2`, which is not in Top-1 for either client, becomes the global Top-1 after the merge. It would have been purged if the clients use threshold T=3, demonstrating degradation that reduces data sizes affects fidelity.

Evaluation: Generated Profiles



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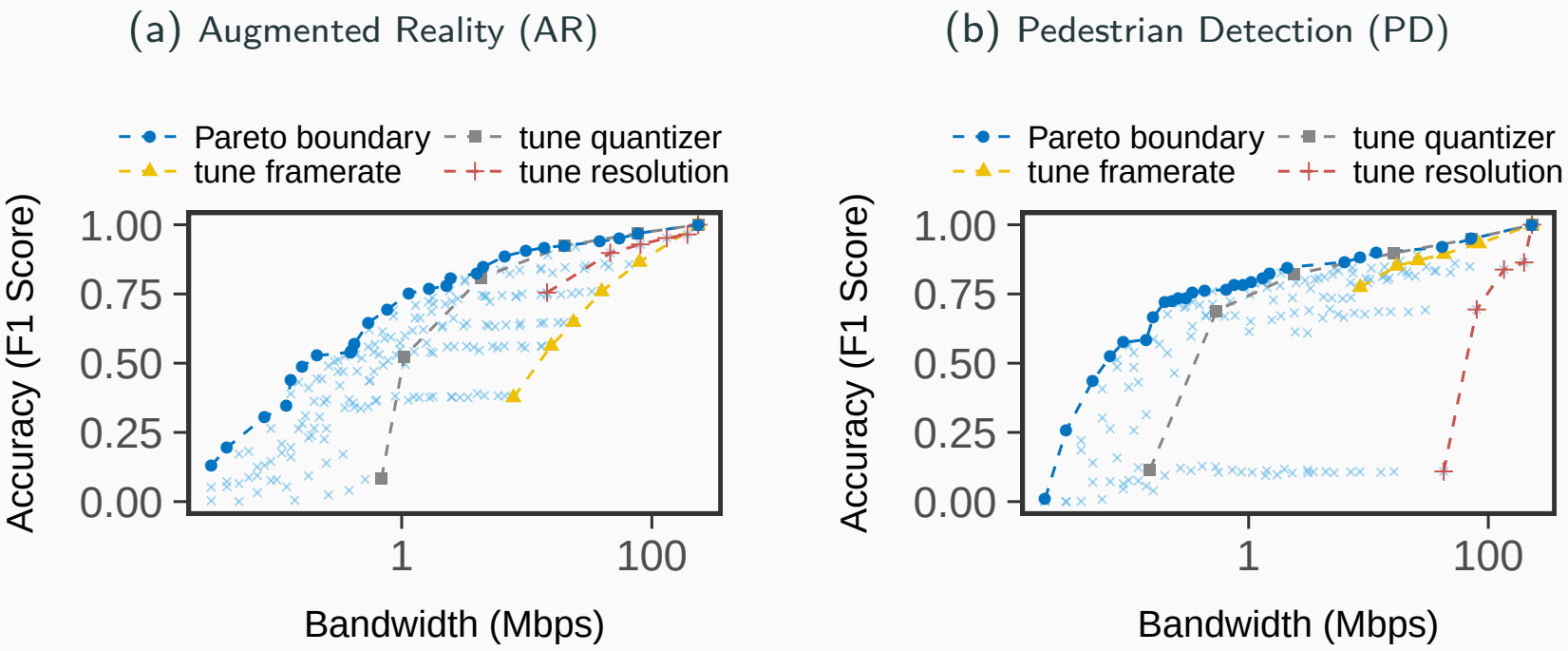

- Optimal strategy is achieved with multiple dimensions; tuning one dimension leads to suboptimal performance.

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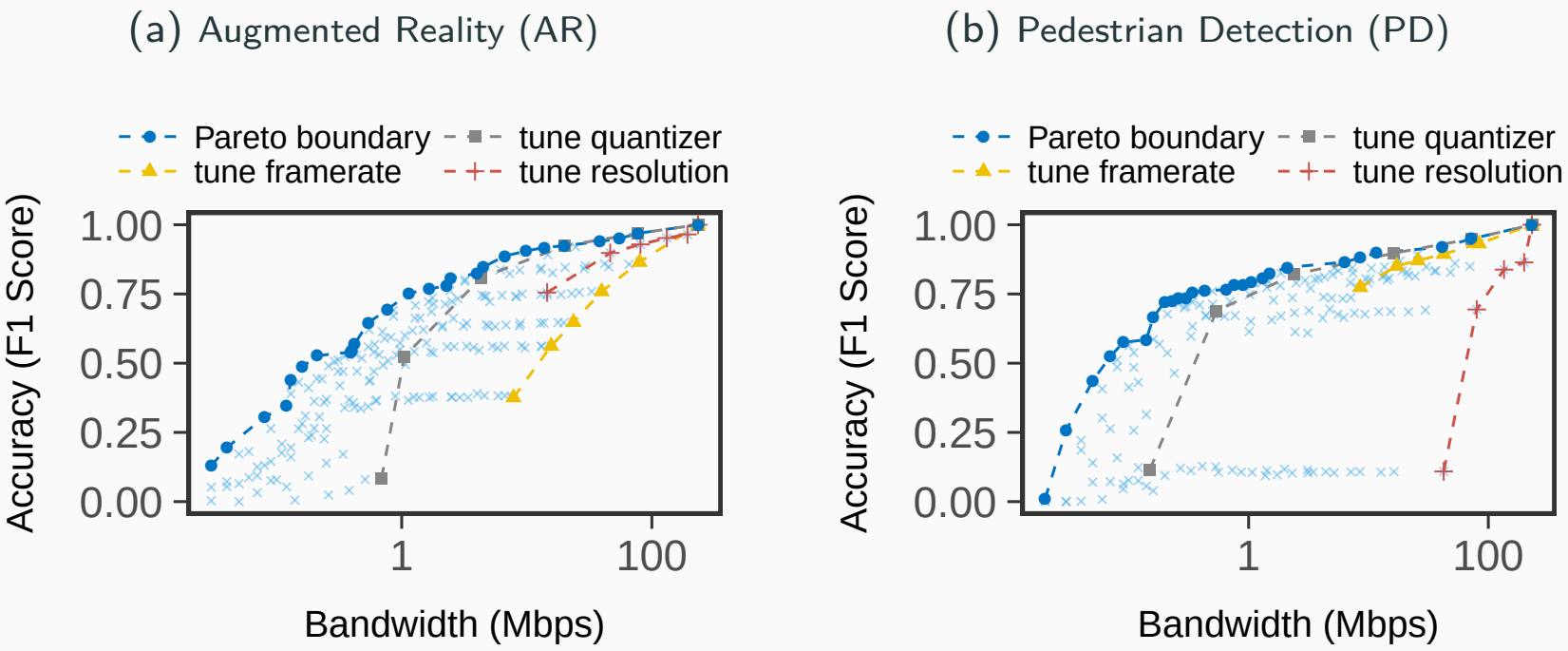

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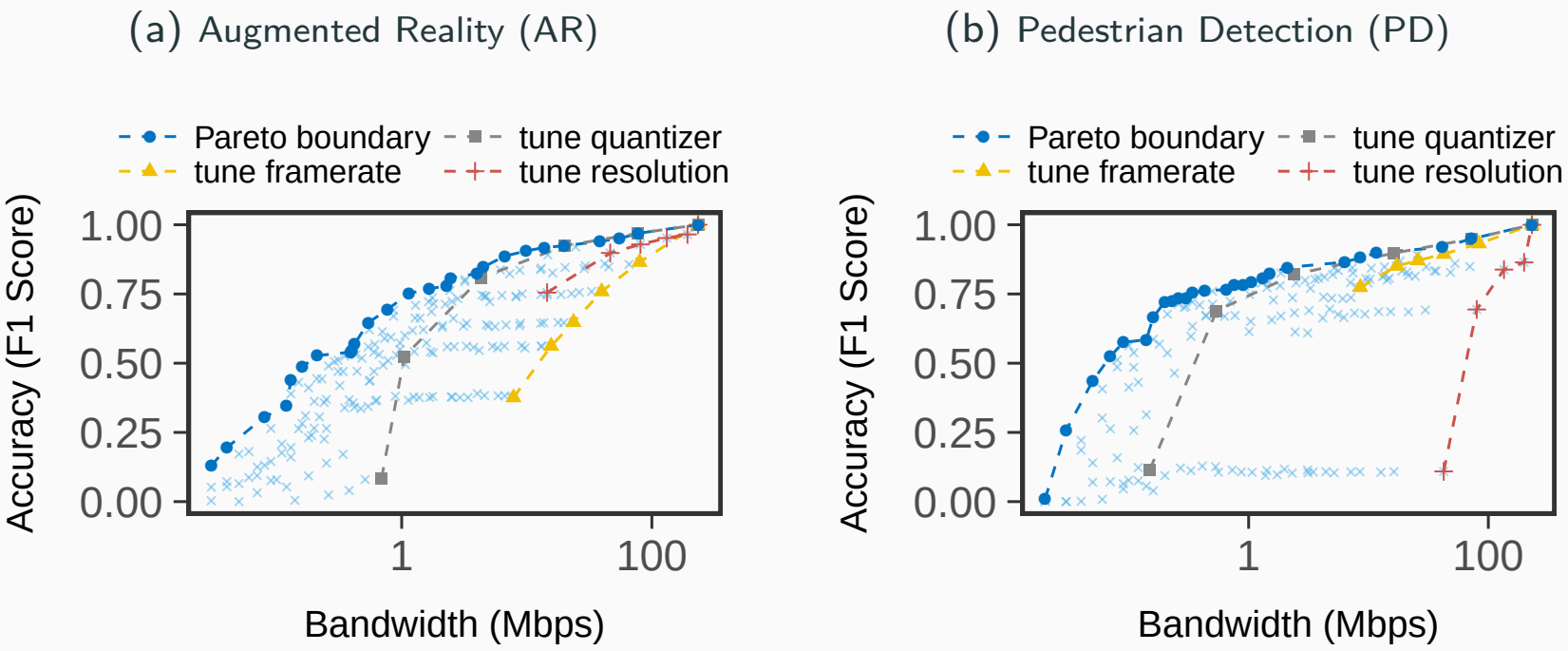

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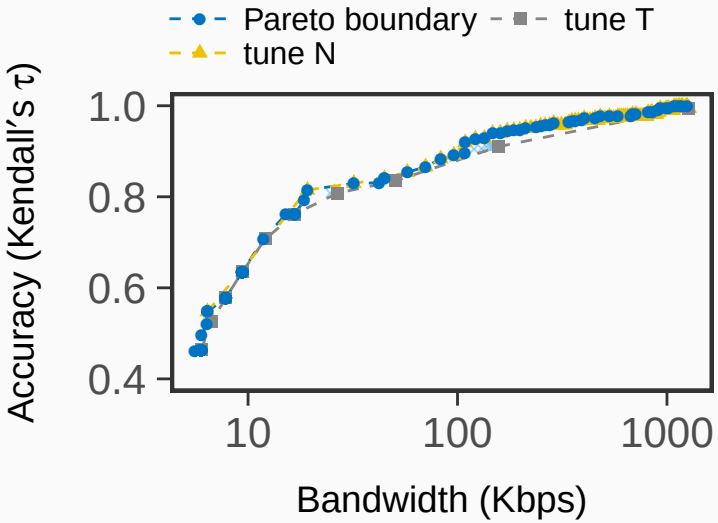

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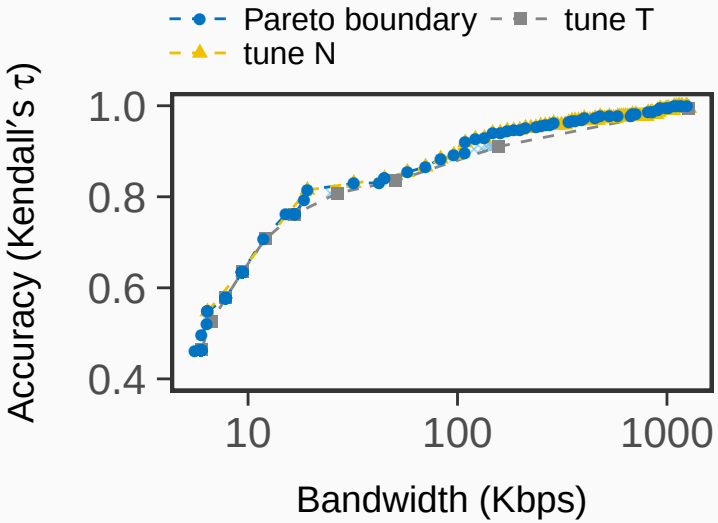

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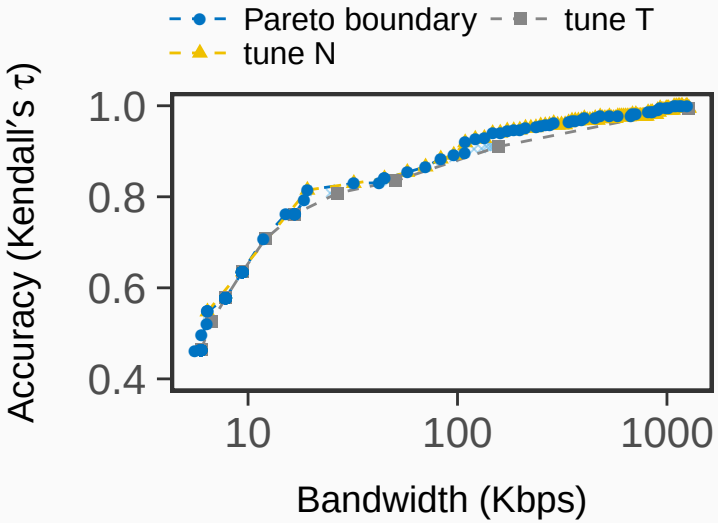

- The effect of each dimension is not significantly different.
- The profile offers quantified effects of degradation.

Evaluation: Runtime Experiment Baselines

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Streaming over TCP	A non-adaptive approach
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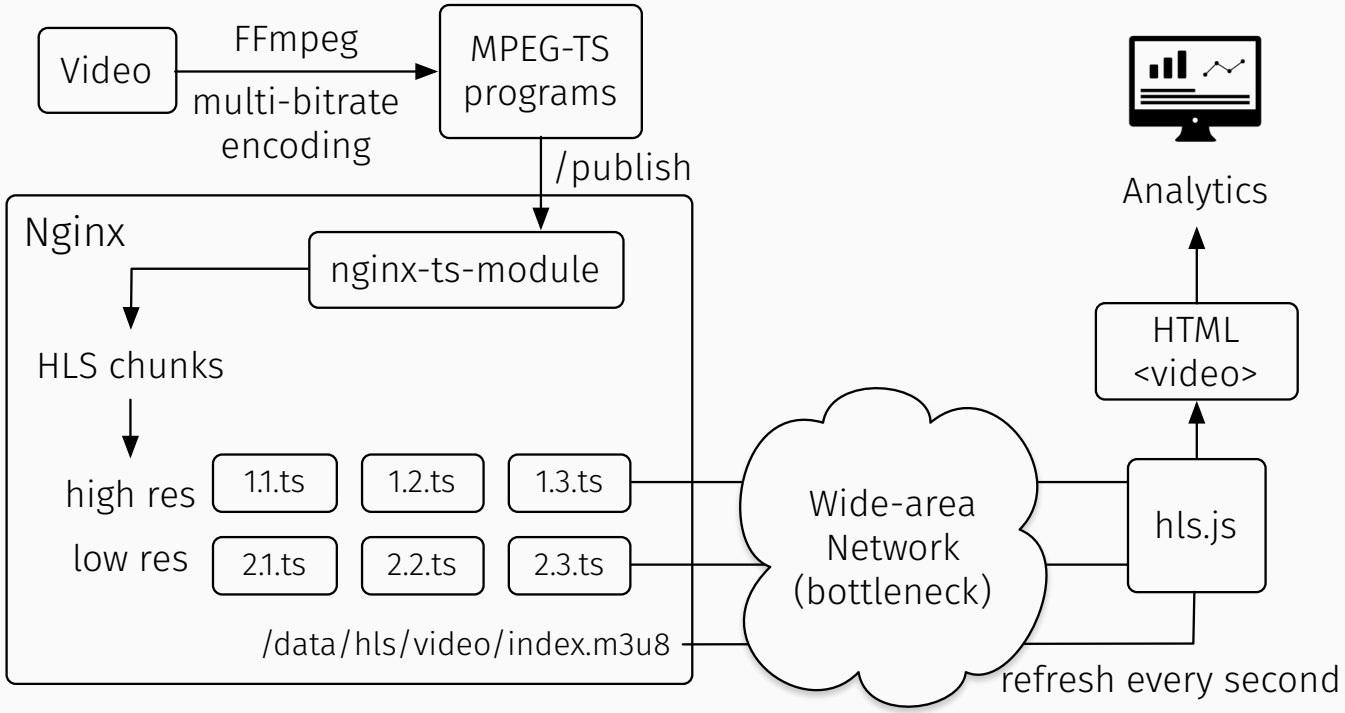
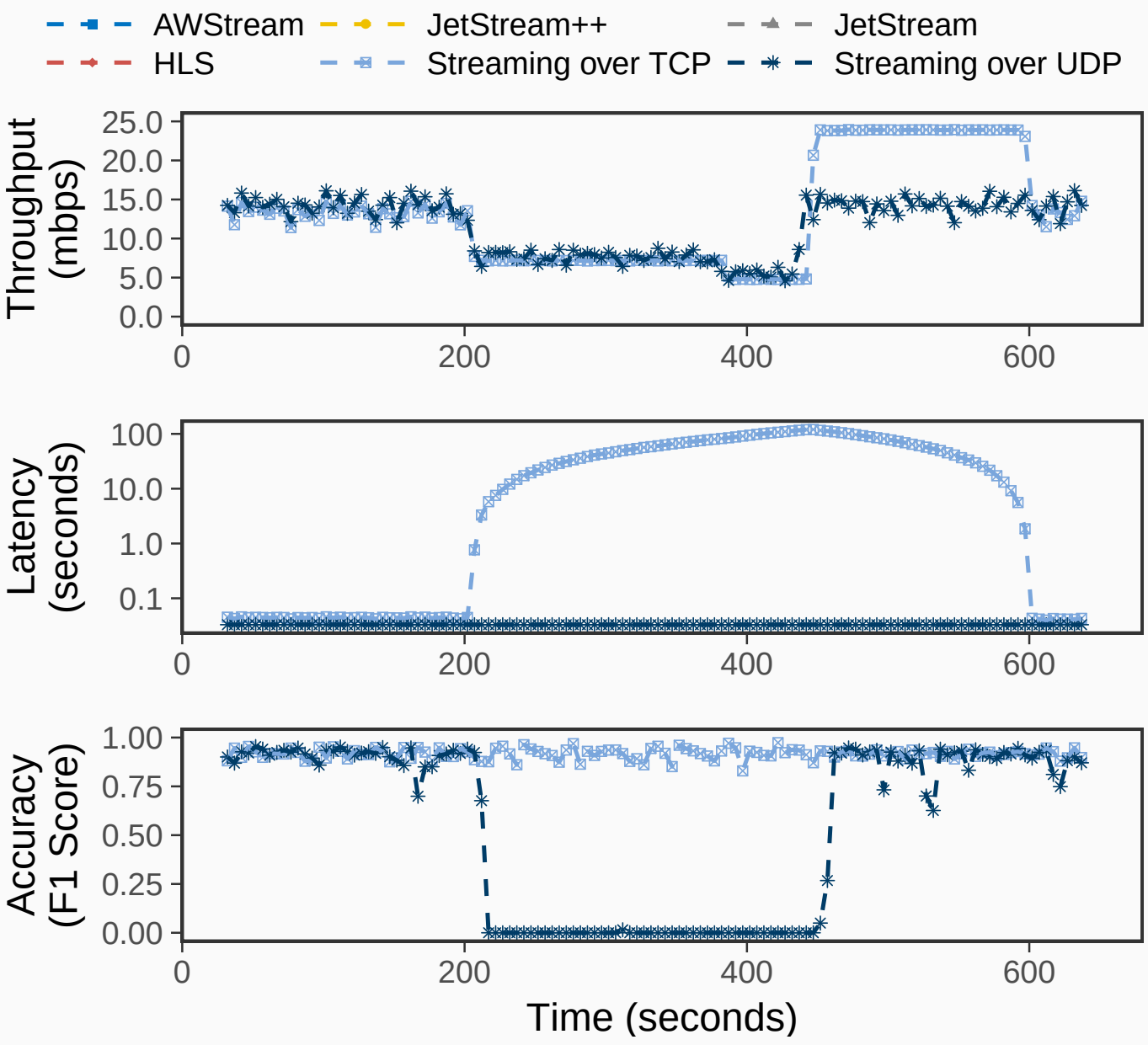
JetStream++	Uses adaptation policy generated by AWStream. JetStream runtime does not probe (hence may oscillate between policies).
HLS [Pantos and May, 2016]	HTTP Live Streaming represents popular adaptive video streaming techniques; used for Periscope video stream [Wang et al., 2016].

Evaluation: Runtime Experiment Baselines



HTTP Live Streaming (HLS) architecture: designed for live video viewing and relying on buffering at the viewing side.

Evaluation: Runtime Performance



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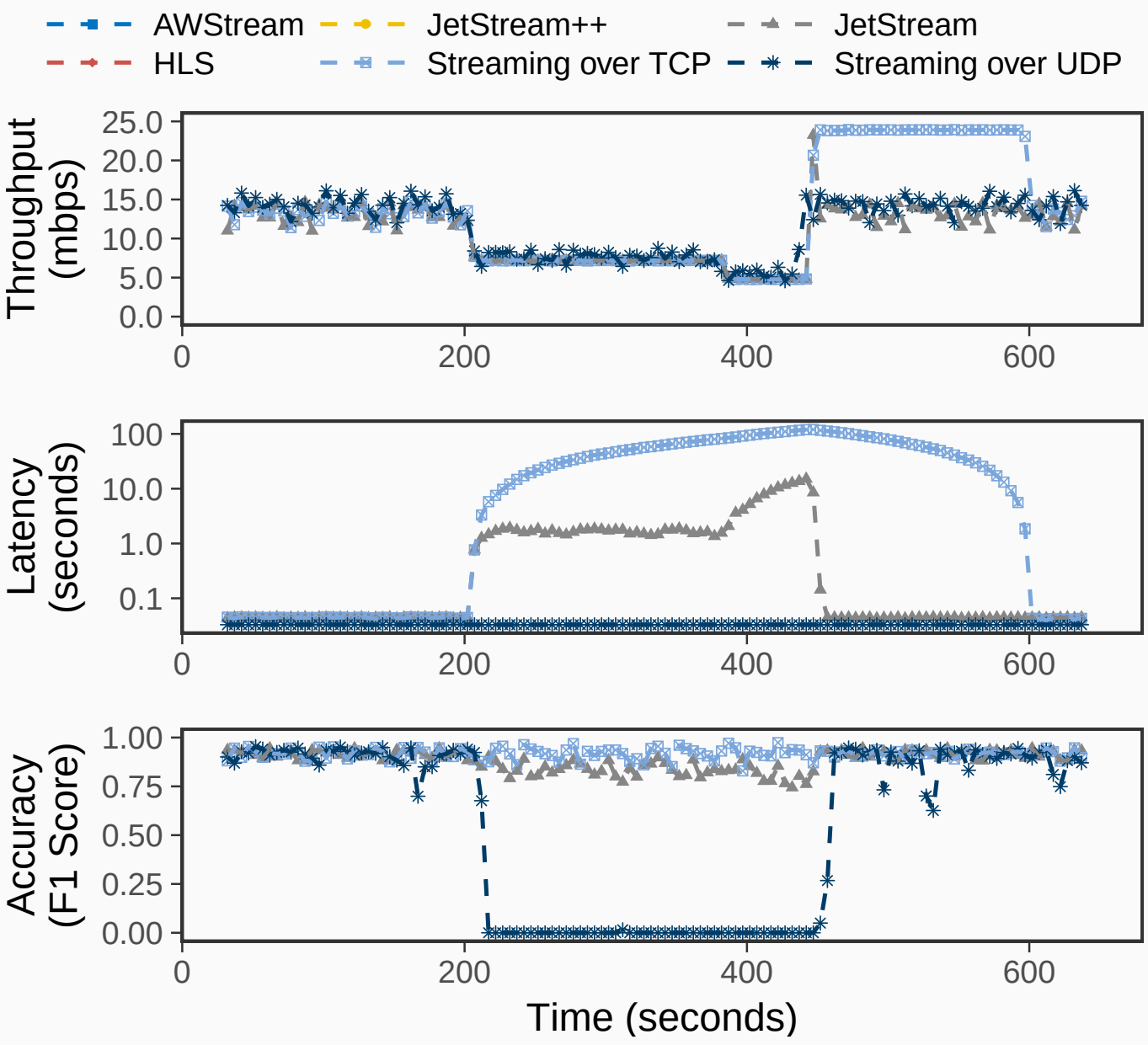

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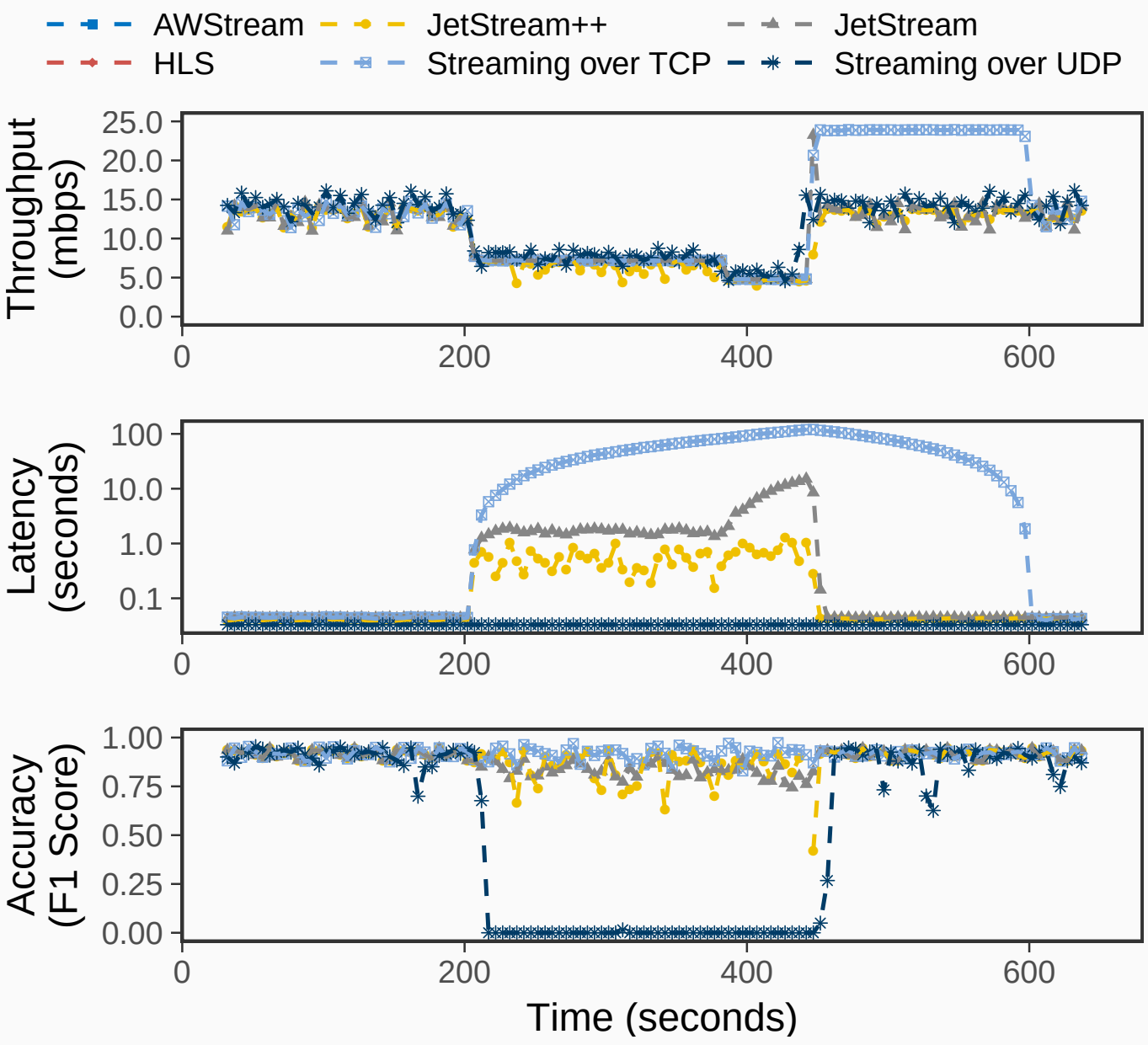

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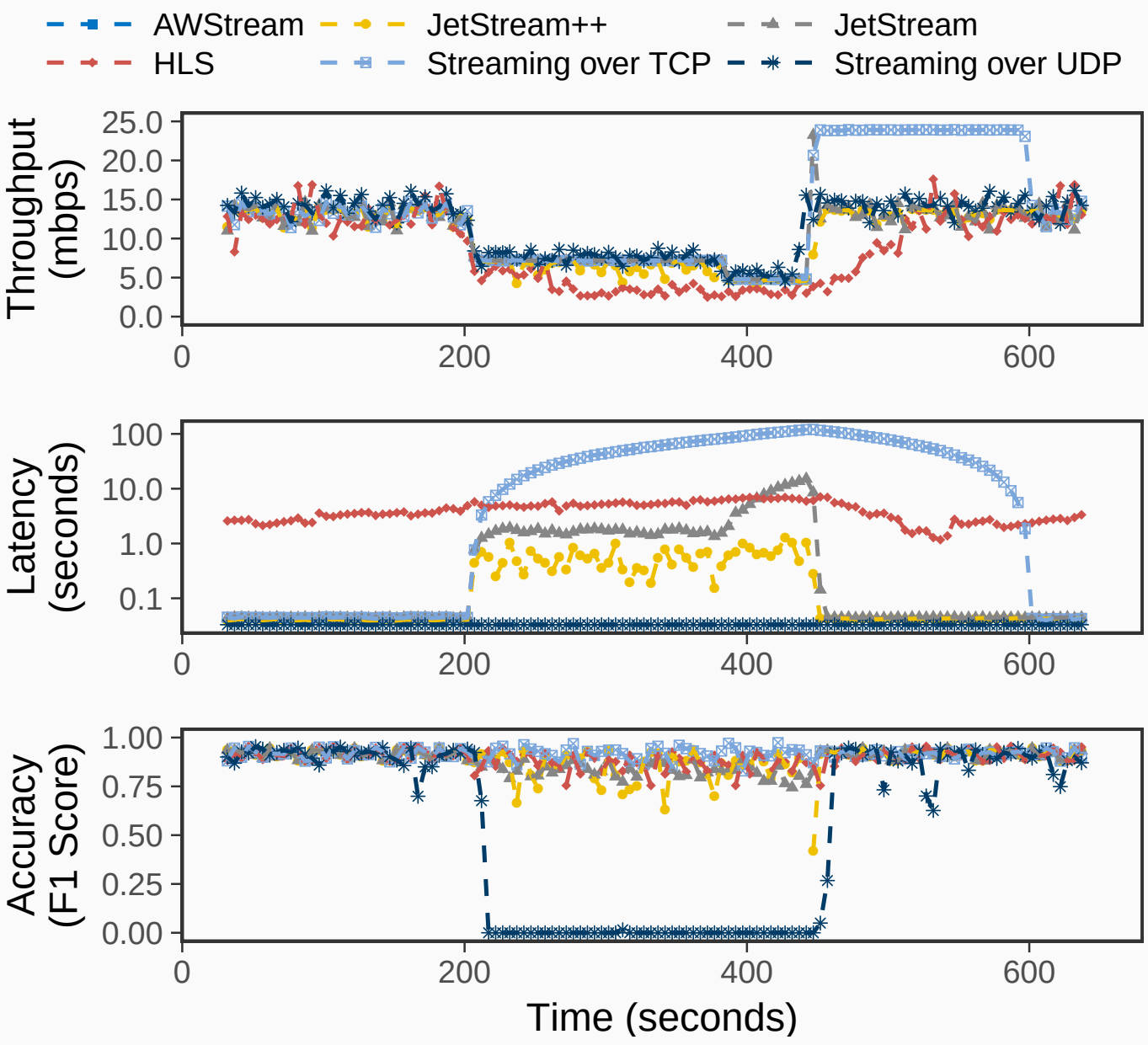

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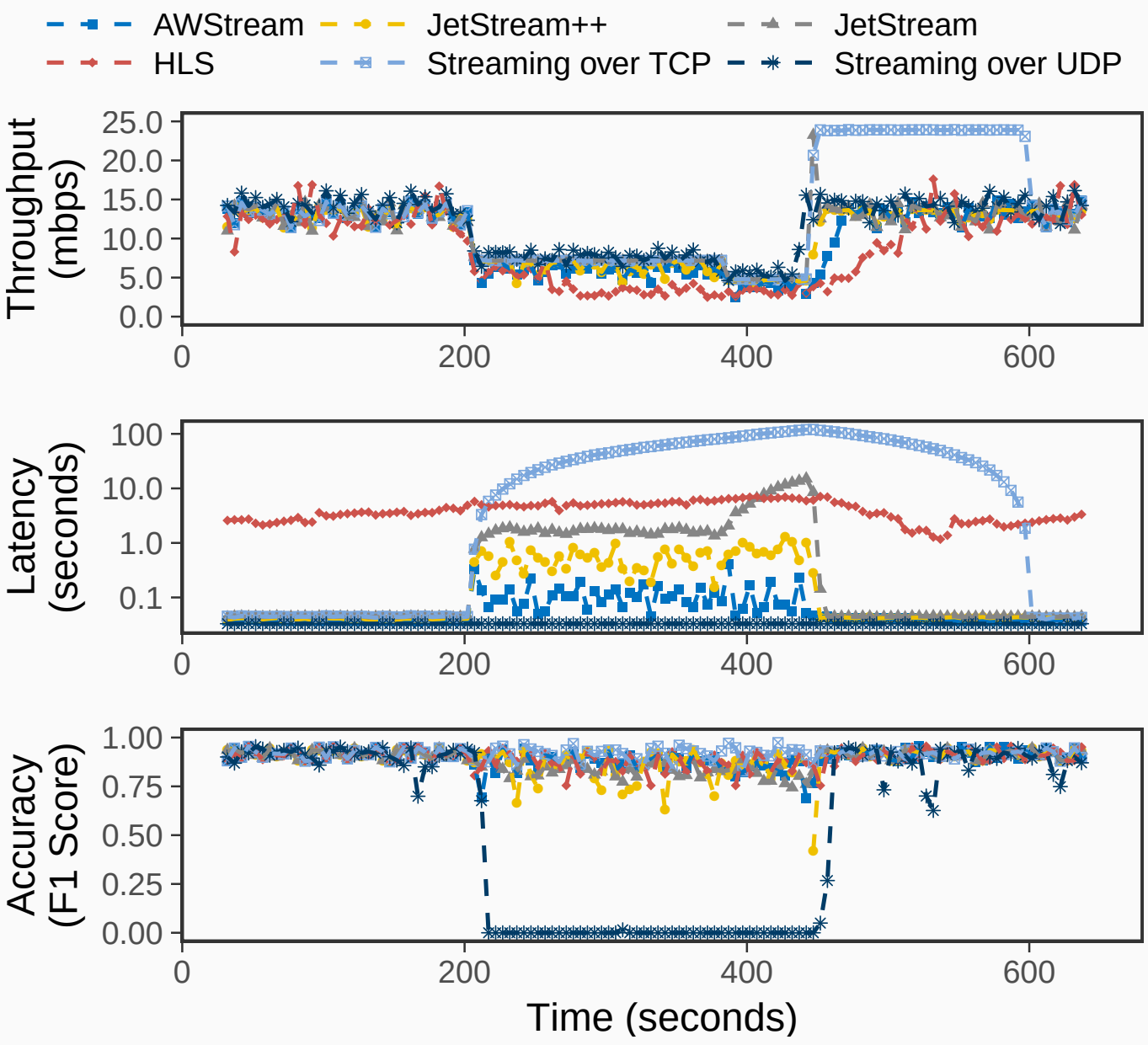

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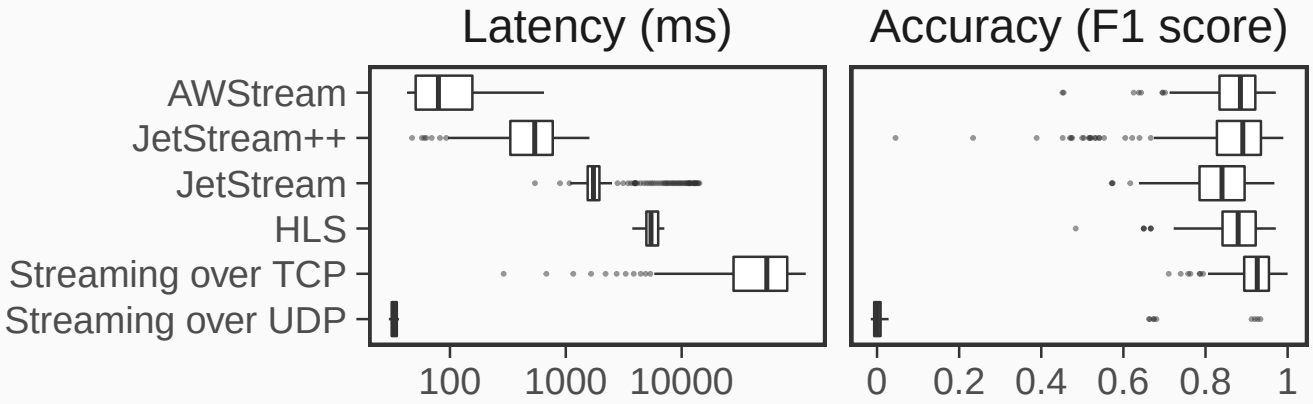

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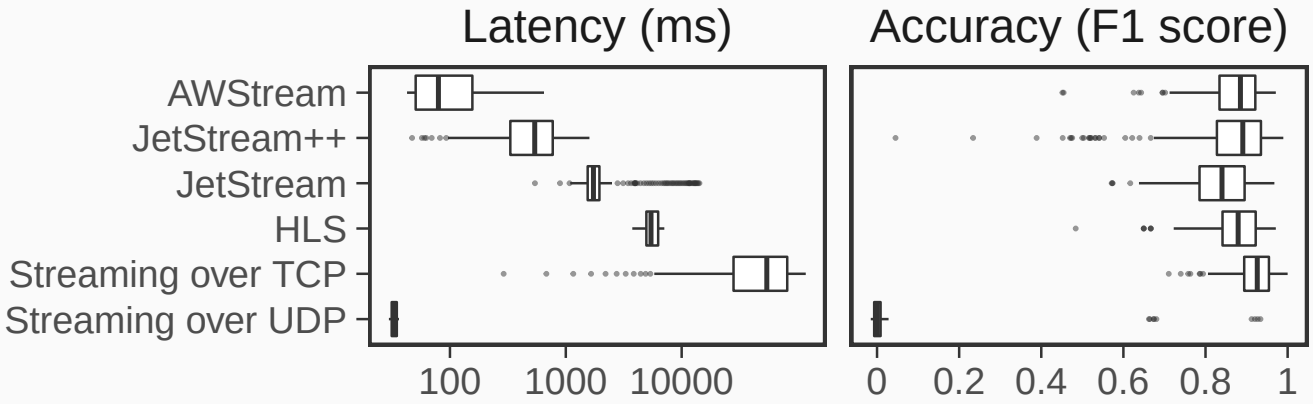

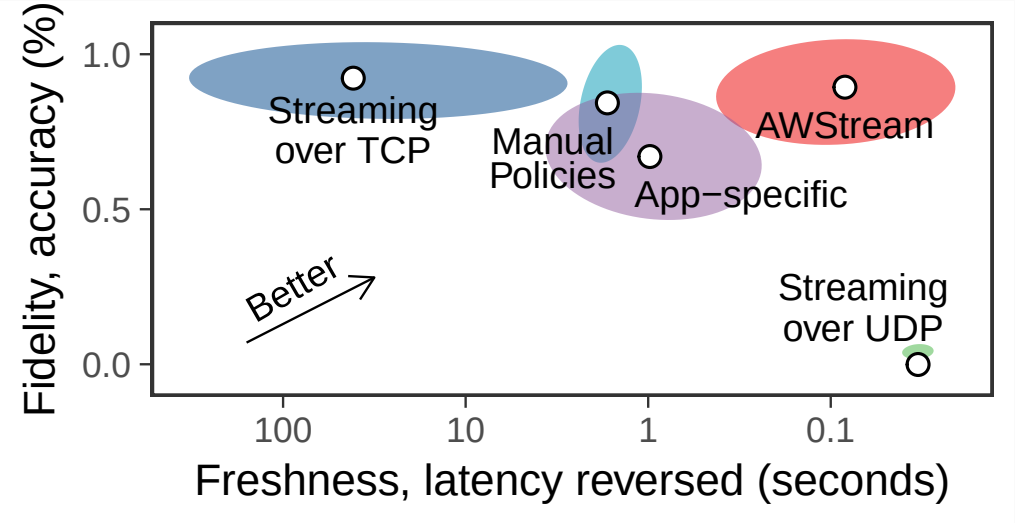

Compute Resource Adaptation

Edge Computing: Fog/Cloudlet/Swarmbox & New Infrastructure

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Cisco Fog Computing [Bonomi et al., 2012]

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Philips Hue Hub

SmartThings

Smartphones

Google onHub

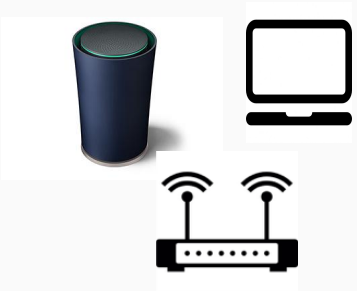
SwarmBox
Intel NUC

Many Gateways

Heterogeneous Environment

IoT / Mobile Devices

Edge Computers (Cloudlet)



Cloud

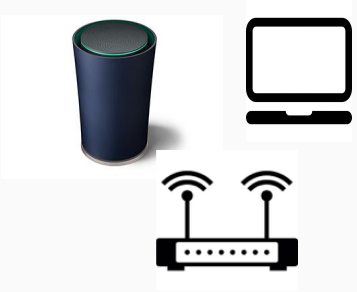
Limited Resources	Compute Power	More Available Resources
Less workload	Workload	More workload Less resource guarantee
Lower latency	Latency	Higher latency Less stable connections

Characteristics of IoT/mobile, edge and cloud

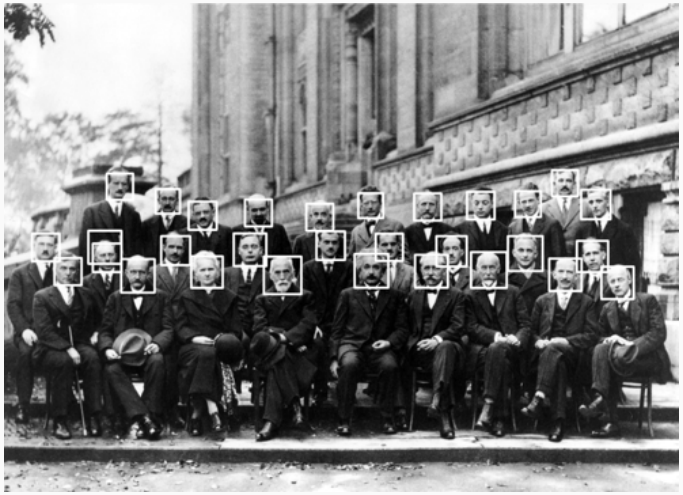
Heterogeneous Environment

IoT / Mobile Devices

Edge Computers (Cloudlet)



Cloud



RPi Model B	Macbook Model A1502	Workstation Xeon E5-1620
4105	544	346

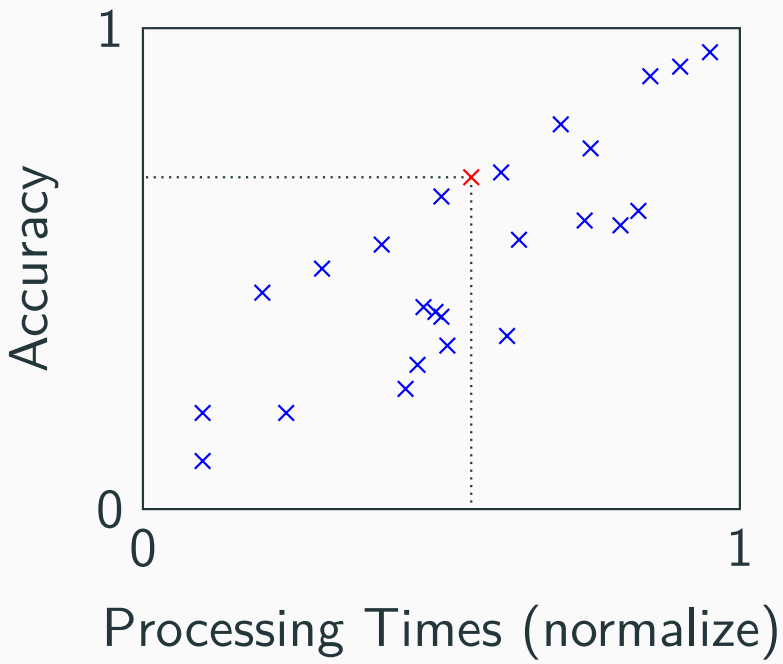
Processing times (ms) on different platforms.

Accuracy and Processing Times Tradeoff

Adaptation

Different algorithm and parameters affect the accuracy and processing times.

Within the tradeoff space, select appropriate algorithm and parameters to meet bounded response time goal.



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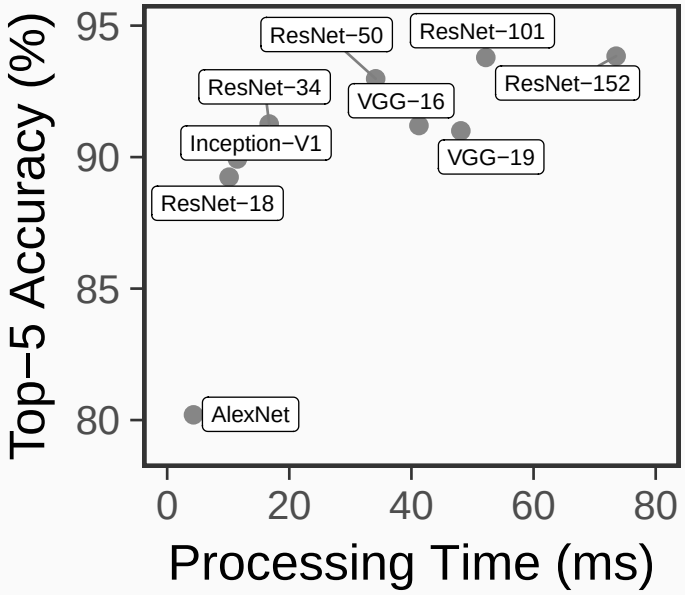

(a) Benchmarks for popular convolutional neural network (CNN) models. Data source: https://github.com/jcjohnson/cnn-benchmarks.

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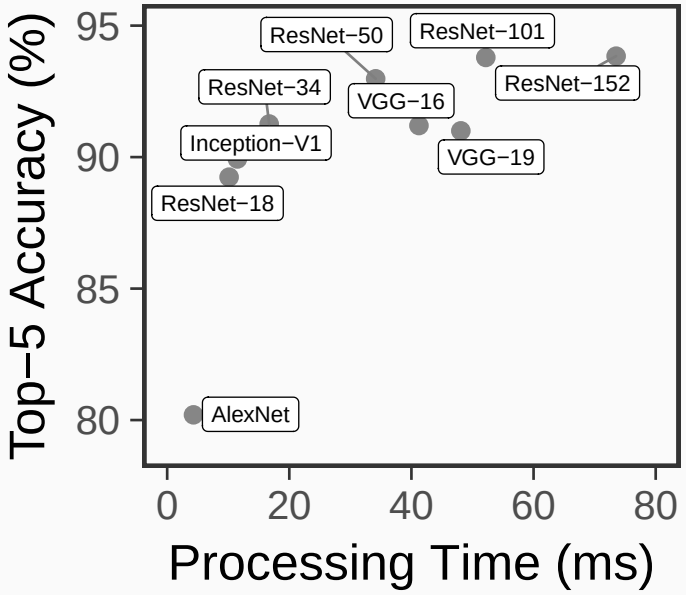

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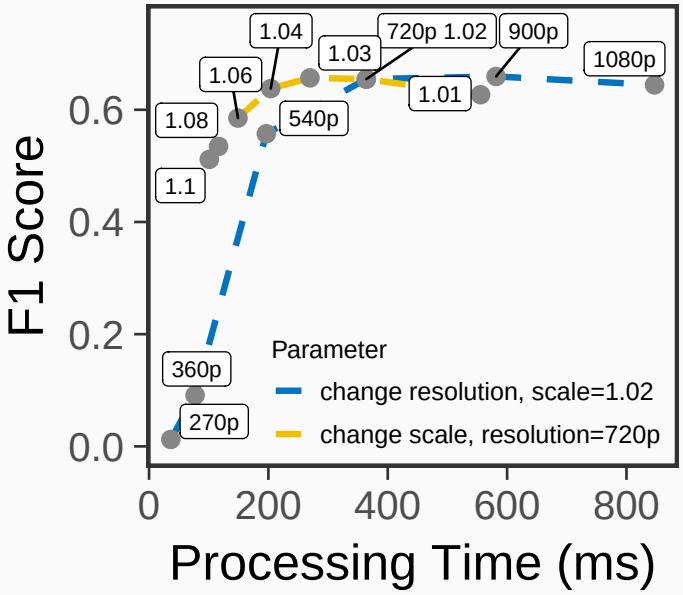

(b) Benchmarks for Viola Jones face detection when changing different parameters (see explanation on the next slide).

detectMultiScale in Viola-Jones (or `CascadeClassifier`)

The OpenCV implementation of Viola-
Jones [Viola and Jones, 2001] has three parameters,

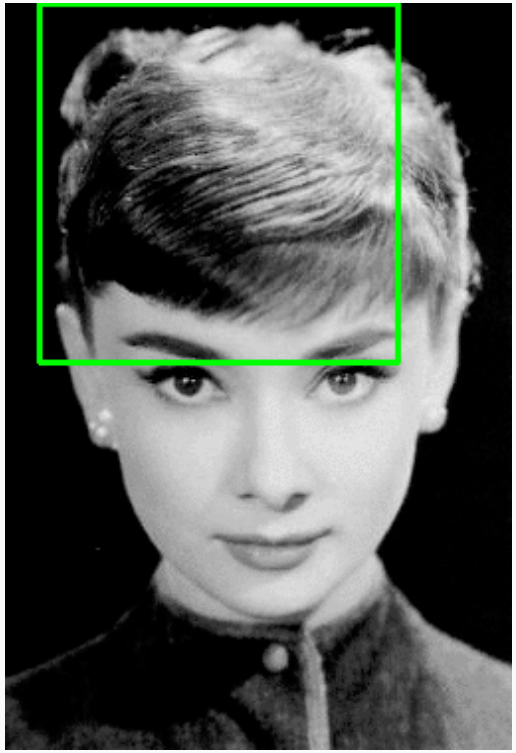

Image Source: pyimagesearch.

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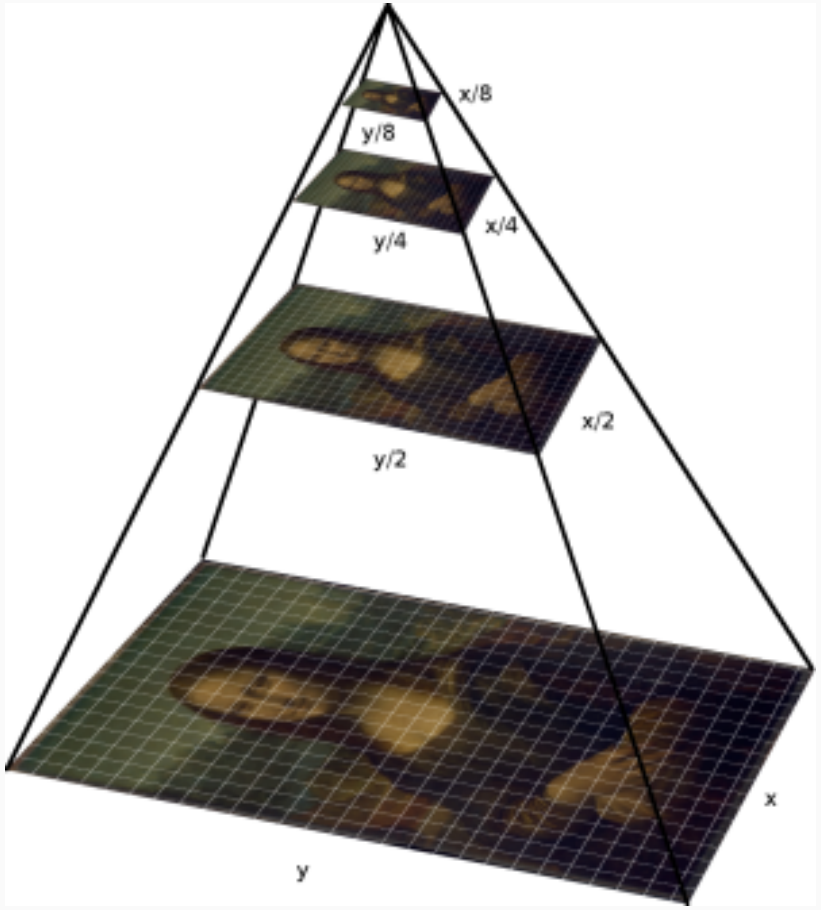

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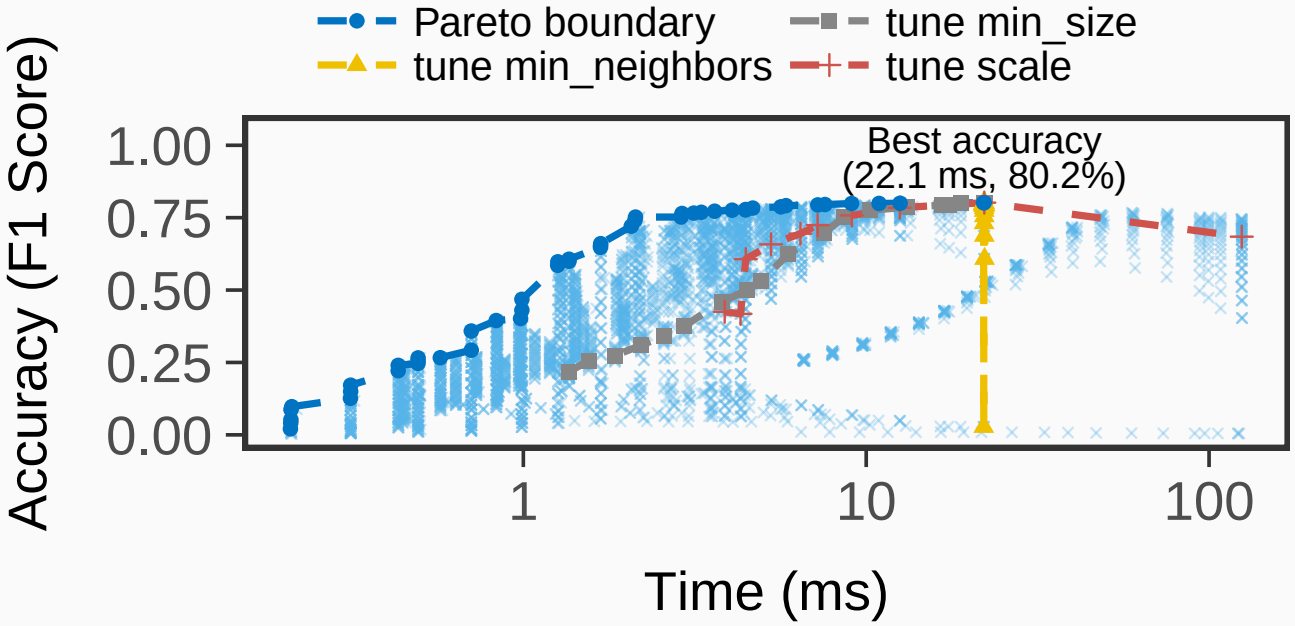
Image Source: Stack Overflow.

Exhaustive Search is Too Expensive



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detectMultiScale in Histogram of Oriented Gradients (HOG)

```
pub struct HogParams {
    pub win_size: Size2i,
    pub block_size: Size2i,
    pub block_stride: Size2i,
    pub cell_size: Size2i,
    pub nbins: c_int,
    pub win_sigma: f64,
    pub l2hys_threshold: f64,
    pub gamma_correction: bool,
    pub nlevels: usize,
    pub hit_threshold: f64,
    pub win_stride: Size2i,
    pub padding: Size2i,
    pub scale: f64,
    pub group_threshold: c_int,
    pub use_meanshift_grouping: bool,
    pub final_threshold: f64,
}
```

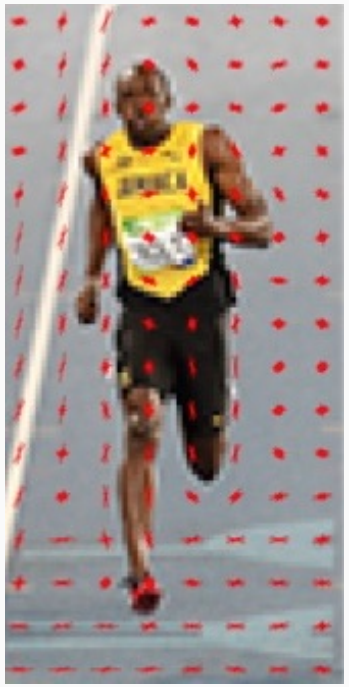

Image Source: learnopencv.com.

Challenges in Adapting Computation

Goal

Adapt computation to different platforms

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   - Profile transfer: refine existing Pareto-optimal points

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Bayesian optimization approximate black-box functions with proxy functions and iteratively proposes new sample point in the large parameter space. Effective for,

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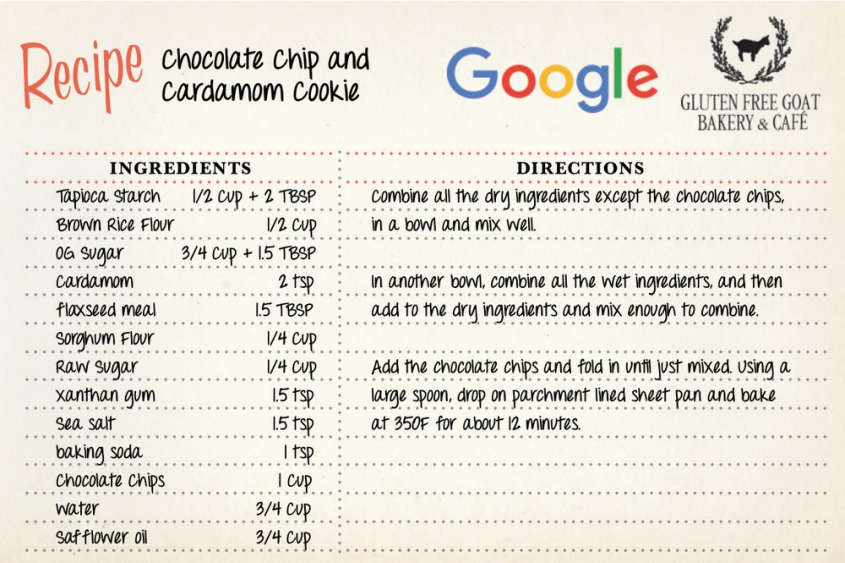


Recipe Chocolate Chip and Cardamom Cookie

Google

GLUTEN FREE GOAT BAKERY & CAFÉ

INGREDIENTS	
Tapioca Starch	1/2 cup + 2 TBSP
Brown Rice Flour	1/2 cup
OG Sugar	3/4 cup + 1.5 TBSP
Cardamom	2 tsp
Flaxseed meal	1.5 TBSP
Sorghum Flour	1/4 cup
Raw Sugar	1/4 cup
Xanthan gum	1.5 tsp
Sea salt	1.5 tsp
baking soda	1 tsp
Chocolate chips	1 cup
Water	3/4 cup
Safflower oil	3/4 cup

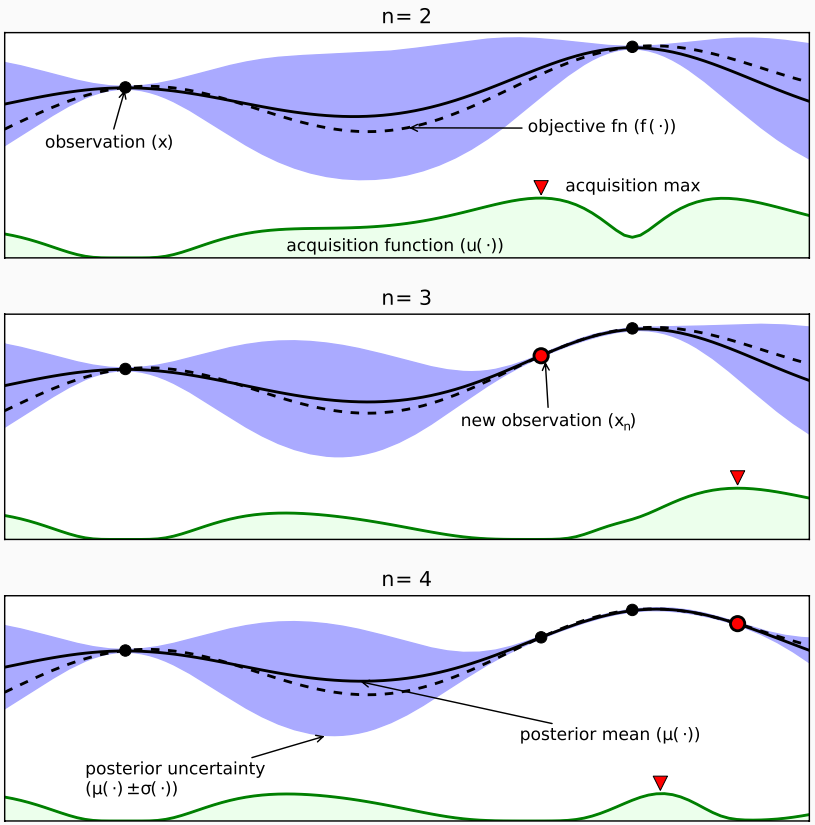
DIRECTIONS

Combine all the dry ingredients except the chocolate chips, in a bowl and mix well.

In another bowl, combine all the wet ingredients, and then add to the dry ingredients and mix enough to combine.

Add the chocolate chips and fold in until just mixed. Using a large spoon, drop on parchment lined sheet pan and bake at 350F for about 12 minutes.

Bayesian Optimization (Illustrated)



Acquisition function evaluates the utility of candidate points for the next evaluation of f, balancing a high objective (exploitation) and high uncertainty (exploration) [Shahriari et al., 2016]

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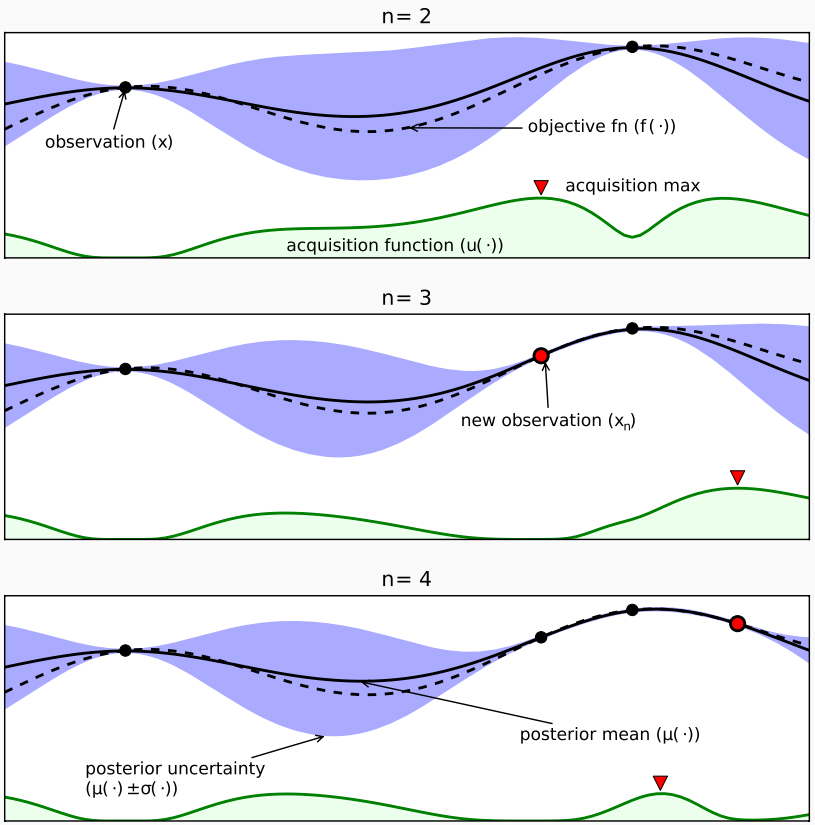

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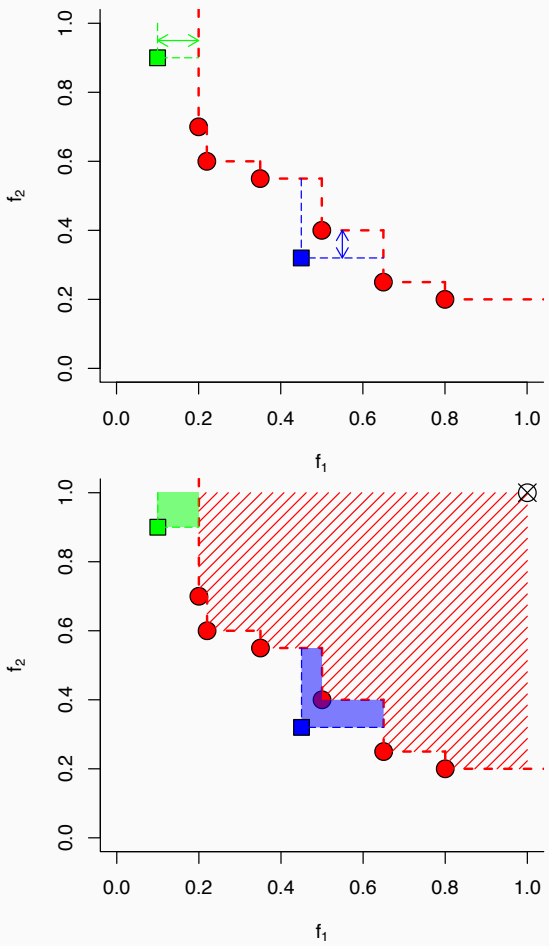

For two-objective optimization, utility gain is based on additive-epsilon (top) or hypervolume (bottom) [Binois and Picheny, 2018]

Bayesian Optimization For Performance Modeling

We use PESMO[2] [Hernández-Lobato et al., 2016] and compare it with two baselines: (1) greedy/coordinate search; (2) random search.

[2] A Python package based on Spearmint. It chooses evaluation points to maximally reduce the entropy of the posterior distribution over the Pareto set.

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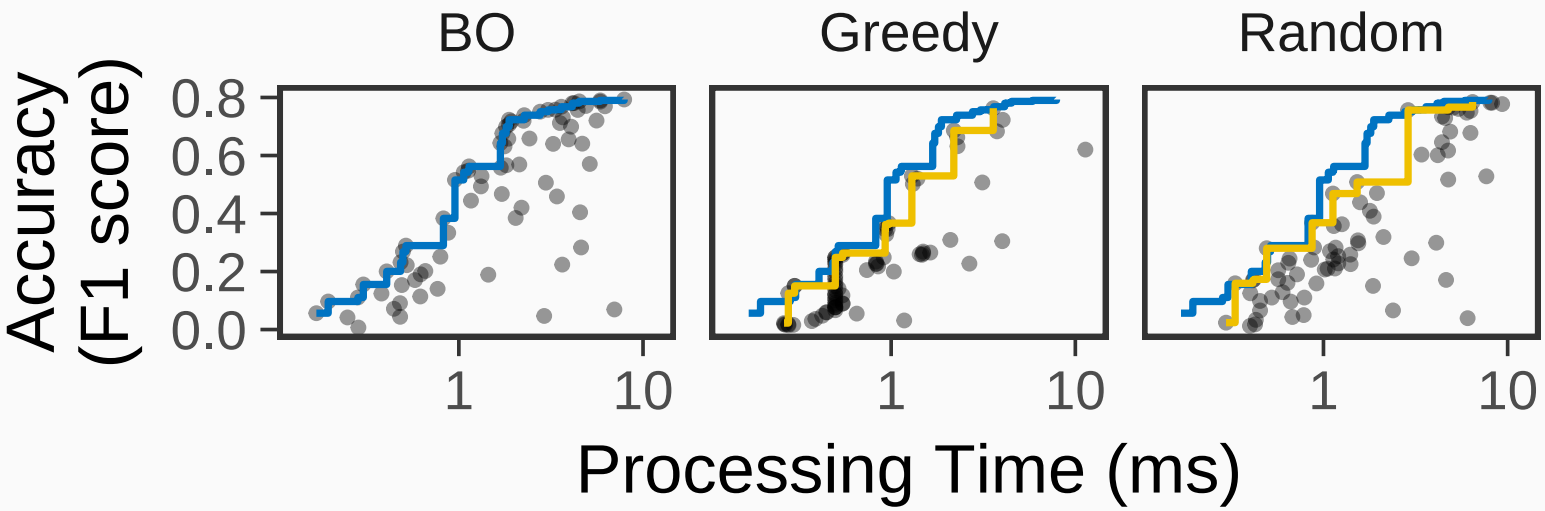

BO evaluates 50 configurations and recommends 29 configurations as the Pareto-optimal boundary (the blue line). Greedy and Random find sub-optimal Pareto configurations with a budget of 80 evaluations (the yellow line in each figure).

[2] A Python package based on Spearmint. It chooses evaluation points to maximally reduce the entropy of the posterior distribution over the Pareto set.

Profile Transfer (without re-running the entire BO)

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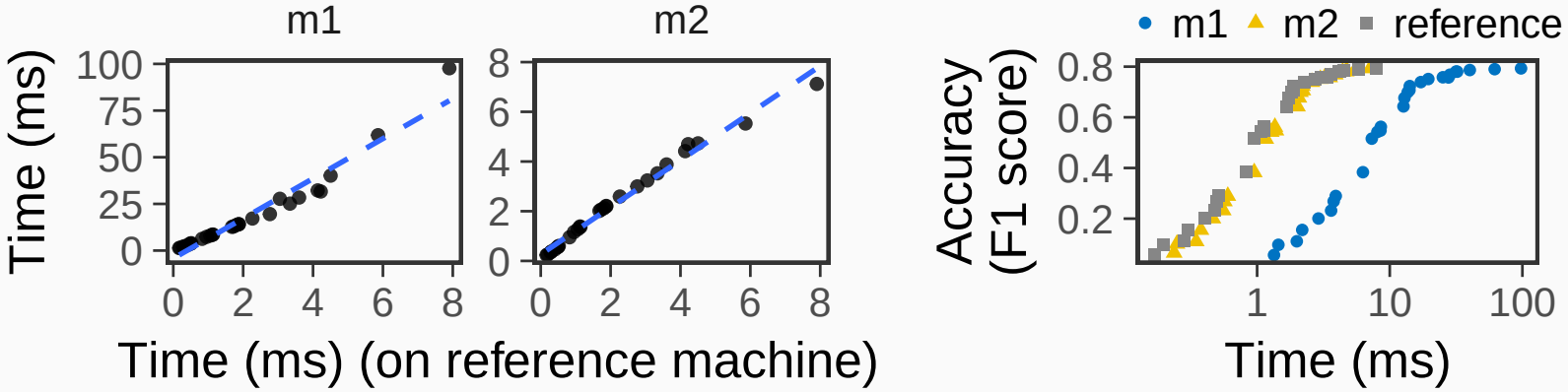

(Left) Empirically, processing times follows a linear approximation. (Right) Stretched/compressed profile. See paper for details.

Conclusion and Acknowledgement

Summary and Contributions

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Summary and Contributions

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- Network resource adaptation
  - Addresses scarce and variable WAN bandwidth
  - Tradeoff between application accuracy and data size demand
- Compute resource adaptation
  - Addresses heterogeneous platforms and large parameter space
  - Tradeoff between application accuracy and processing times
- Overall, a systematic and quantitative approach for adaptation

Current (other) and Future Work

TerraSwarm Vision

TerraSwarm applications are characterized by their ability to dynamically recruit resources such as sensors and data from the cloud, aggregate and use that information to make or aid decisions.

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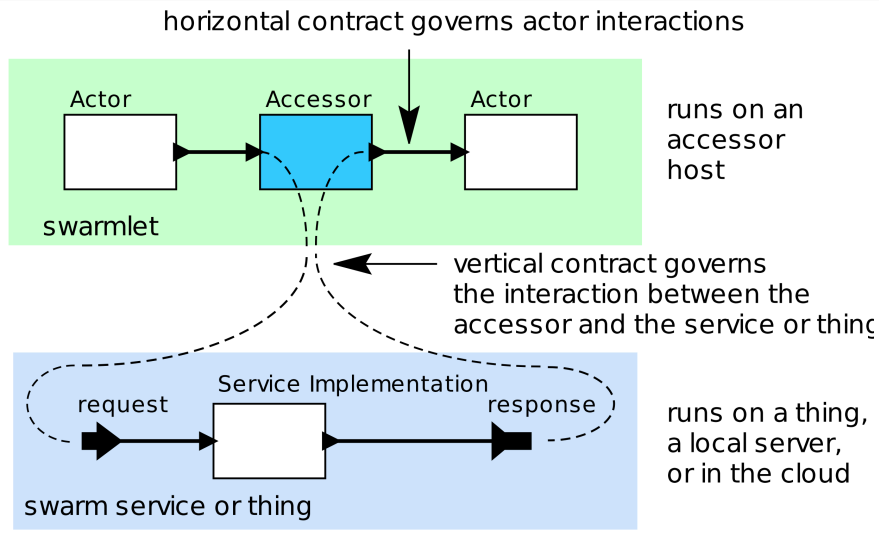
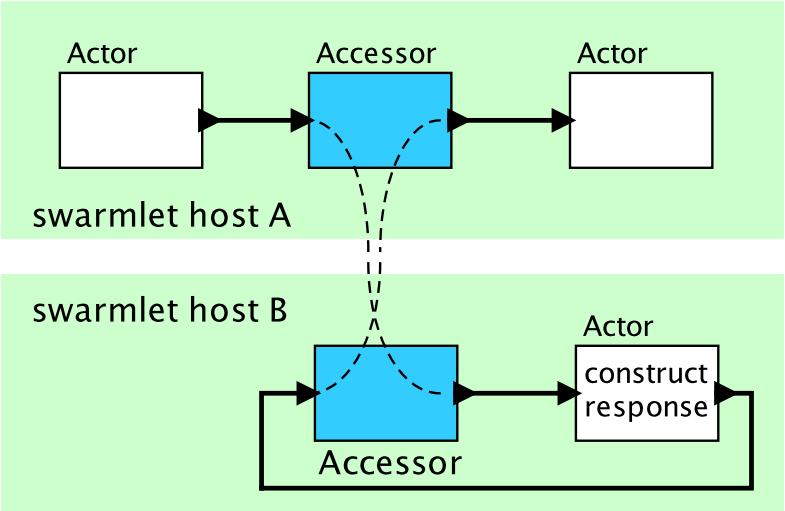


(a) Accessor in a network of actors.



(b) Instantiate accessors on another host.

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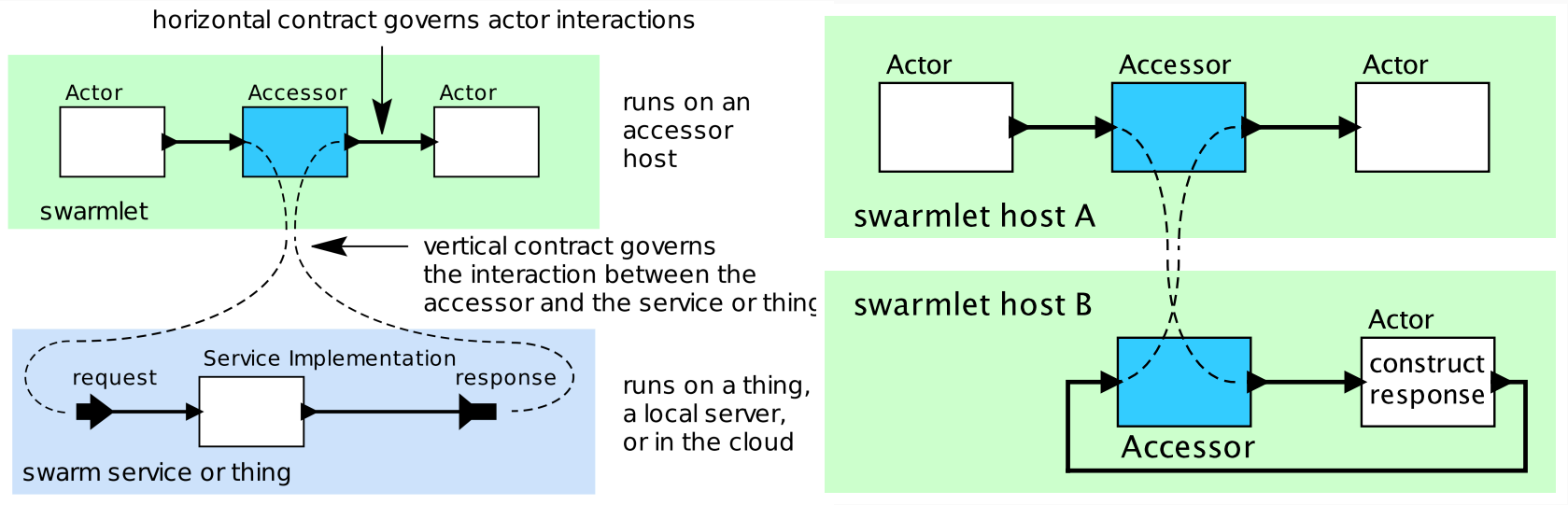

(a) Accessor in a network of actors.

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Work in progress with Marten and Andrés. Maybe checkout Marten's dissertation talk in the future :)

Acknowledgment

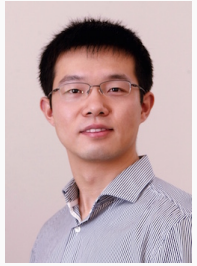

Prof. Edward Lee


Prof. John Wawrzynek


Prof. John Chuang


Prof. Sylvia Ratnasamy


Prof. Björn Hartmann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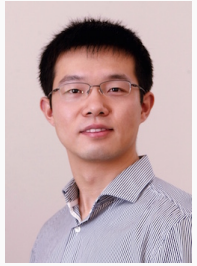
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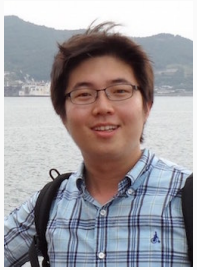
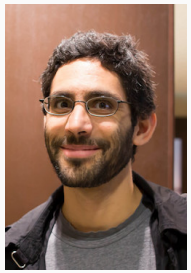

Dr. Hokeun Kim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Dr. Chris Shaver


Antonio Iannopollo


Kaifei Chen

The entire EAL research group (with many visiting scholars)

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♡

1N73LL1G3NC3

15 7H3

4B1L17Y

70 4D4P7 70

CH4NG3

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Image Source: 0stees.com

Google Network Infrastructure

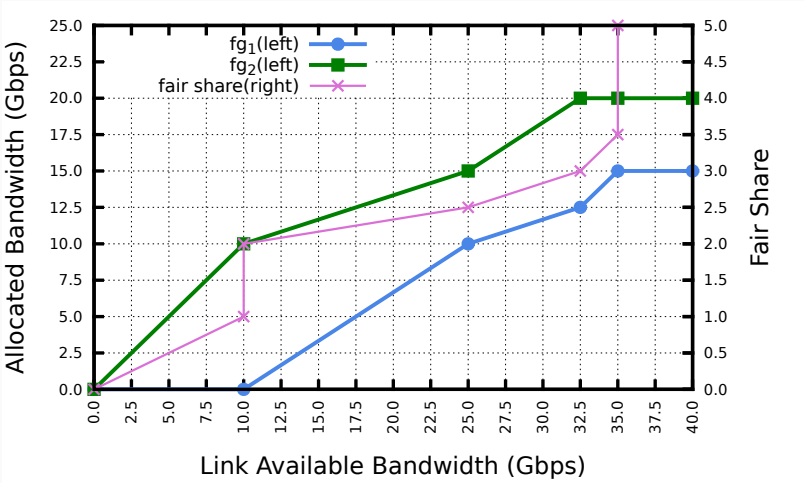

Figure 4: Bandwidth Sharing on a Bottleneck Link.

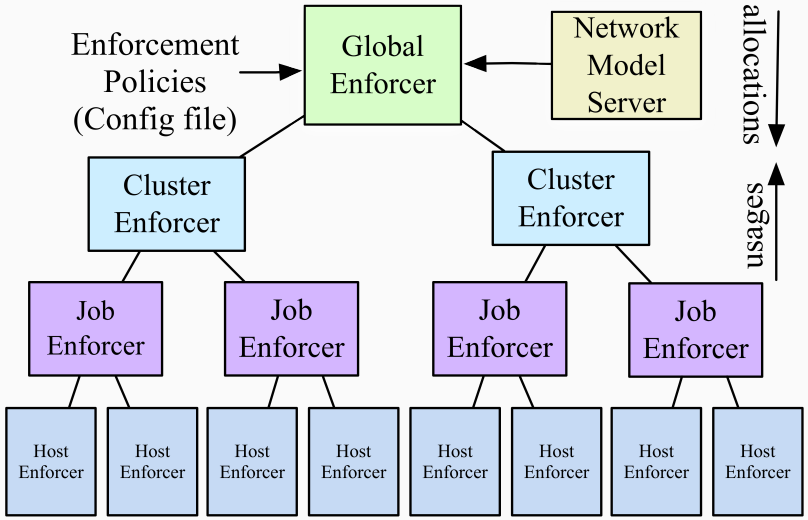

Figure 5: BwE Architecture.

BwE: Flexible, Hierarchical Bandwidth Allocation for WAN Distributed Computing [Kumar et al., 2015]

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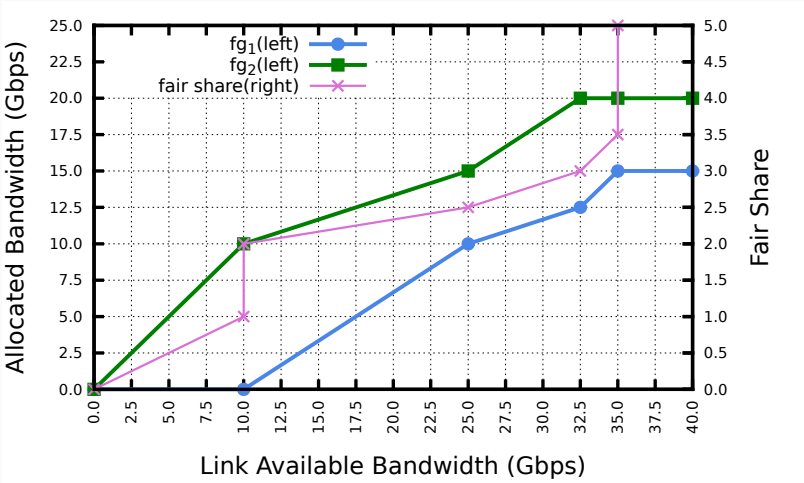

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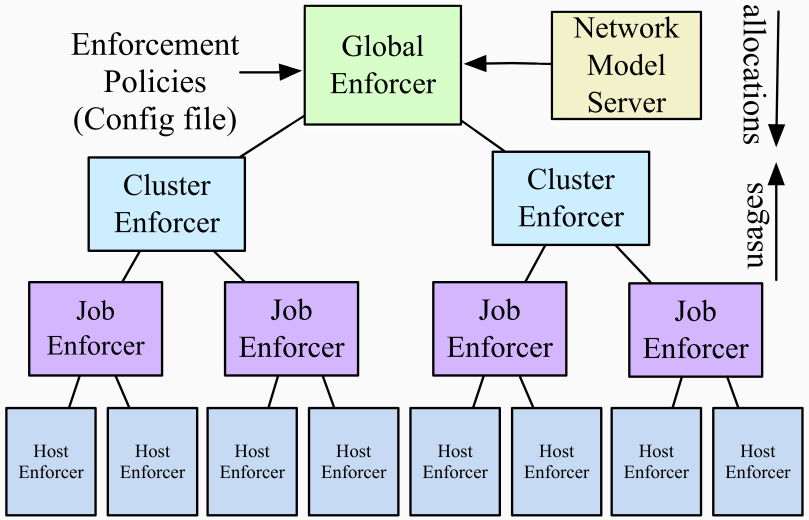

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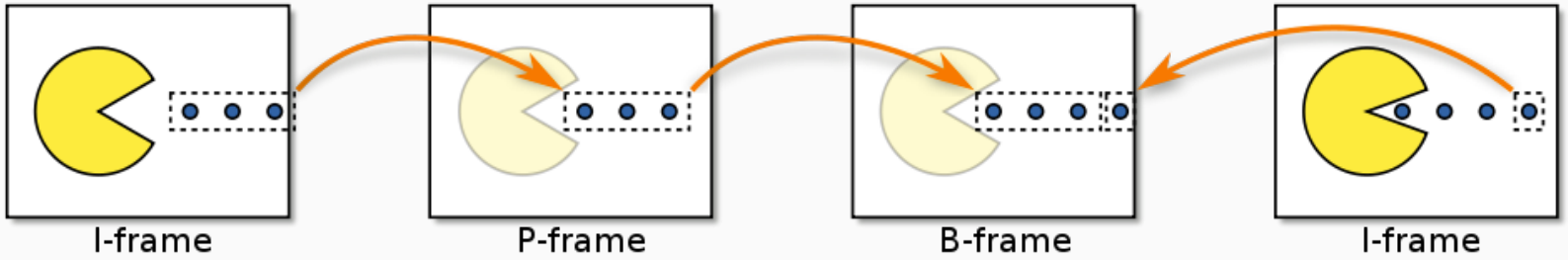
Move from Lagrangian to Eulerian (ask Edward if you don't know what these words refer to).

Backup Slides.

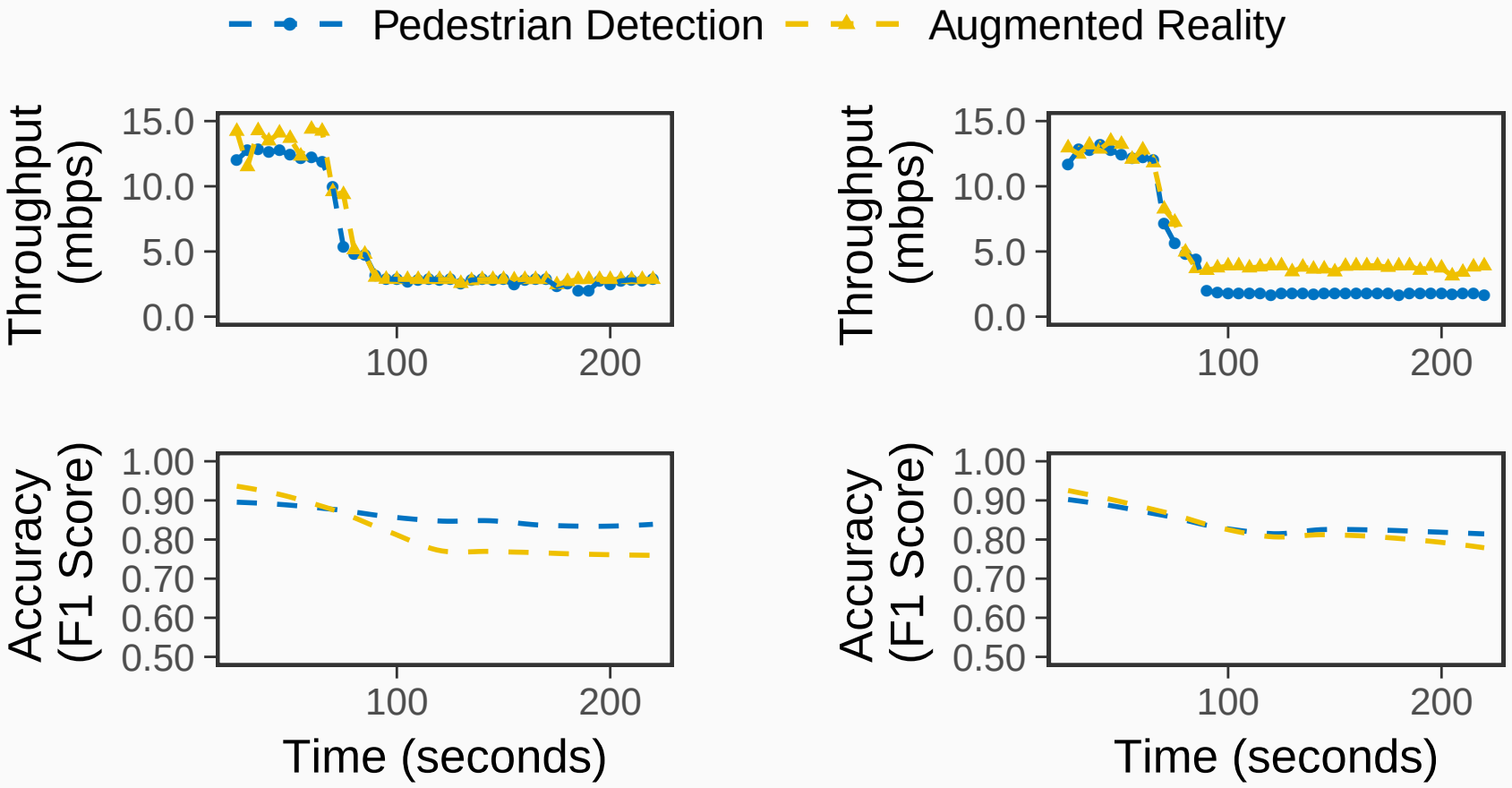
Video Encoding Frames



PC: https://en.wikipedia.org/wiki/Video_compression_picture_types

- **I-frames** are the least compressible but don't require other video frames to decode. I-frames are further compressed with quantization.
- **P-frames** can use data from previous frames to decompress and are more compressible than I-frames.
- **B-frames** can use both previous and forward frames for data reference to get the highest amount of data compression (not an option in live streaming).

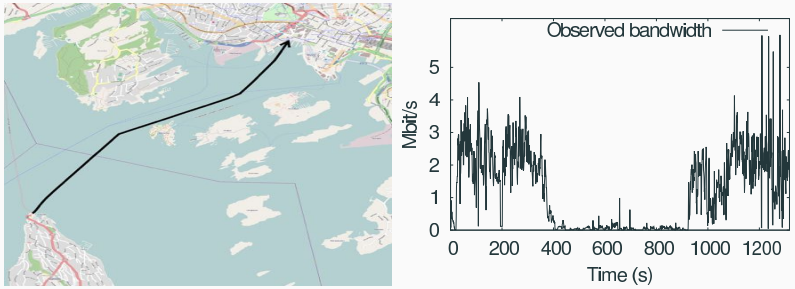
Evaluation: Resource Allocation for Multiple Applications



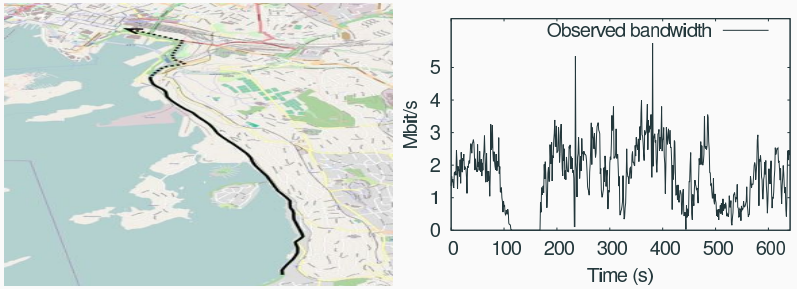
(a) Resource Fairness

(b) Utility Fairness

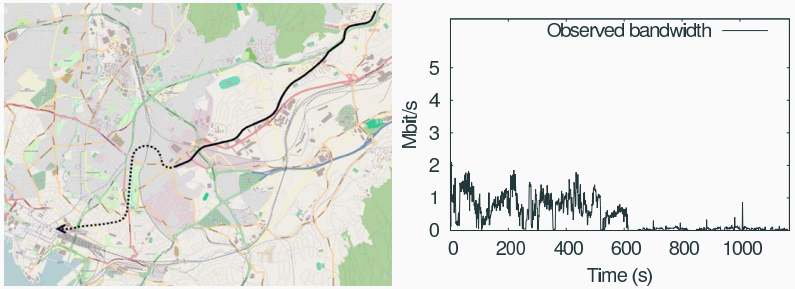
Bandwidth Fluctuations (Cellular)



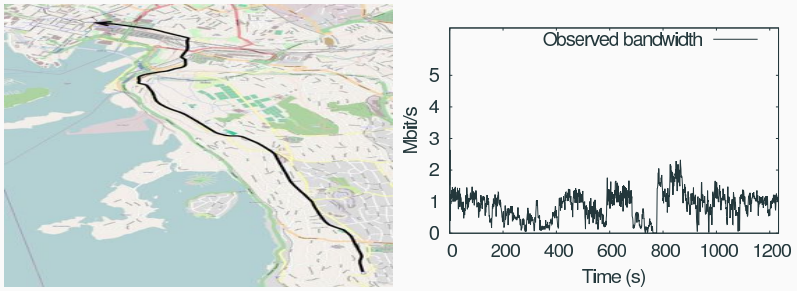
(a) Ferry



(c) Bus



(b) Metro (dotted line in tunnel)



(d) Tram

Riiser, Haakon, et al. "A comparison of quality scheduling in commercial adaptive HTTP streaming solutions on a 3G network." Proceedings of the 4th Workshop on Mobile Video. ACM, 2012.

Bandwidth Fluctuations (WiFi)

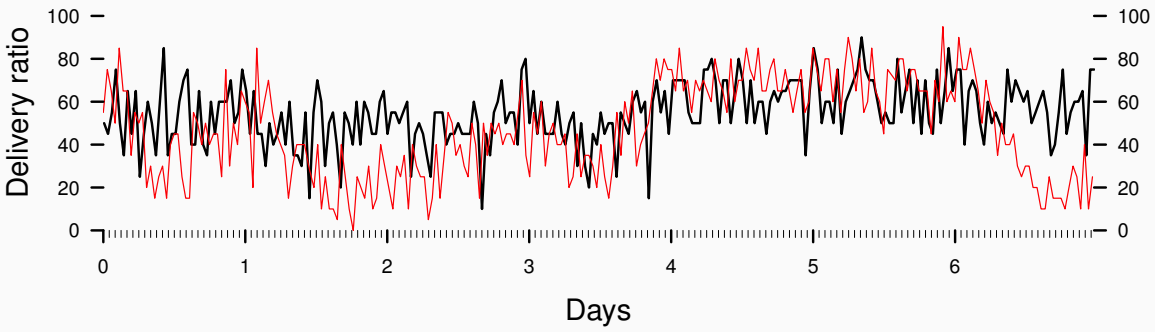


Figure 4: Delivery ratio variation over a week for two randomly chosen 2.4 GHz links.

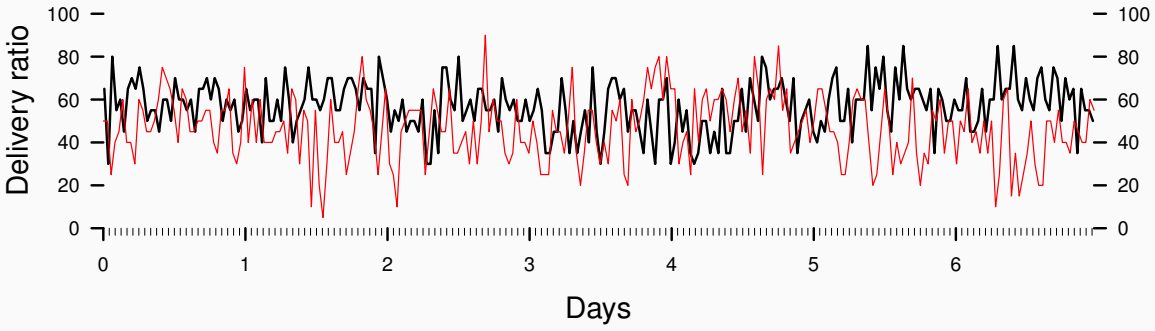


Figure 5: Delivery ratio variation over a week for two randomly chosen 5 GHz links.

Biswas et al, Cisco Meraki, Large-scale Measurements of Wireless Network Behavior, SIGCOMM'15. Two randomly chosen links.

Continue with the main slides.

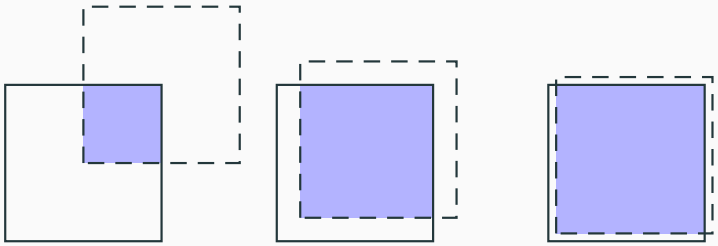
Augmented Reality

- Training and testing data characteristics
  - 1920x1080 resolution with 30 FPS
  - training: 707 frames (23.5 seconds), testing: 1384 frames (46 seconds)
- Object Recognition
  - Darknet: Open Source Neural Networks in C
  - Developed by Joseph Redmon, "Do whatever you want with it" license
  - It supports CPU/GPU
  - In this work, I am using a pre-trained model with Coco dataset
- Other systems such as TensorFlow, Caffe would also work

IOU and F1

Positive if intersection over union (IOU) larger than 0.5.

$$\text{IOU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$



(a) IOU=0.14 (b) IOU=0.57 (c) IOU=0.82

F1 is the harmonic mean of precision and recall:

	P	N
Y	True Positive	False Positive
N	True Positive	False Positive

$$\text{Precision} = \frac{\text{true positive}}{\text{all positive}}$$

$$\text{Recall} = \frac{\text{true positive}}{\text{all detection}}$$

$$\text{F1} = \frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$$

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