Cross-Camera Inference on the Constrained Edge

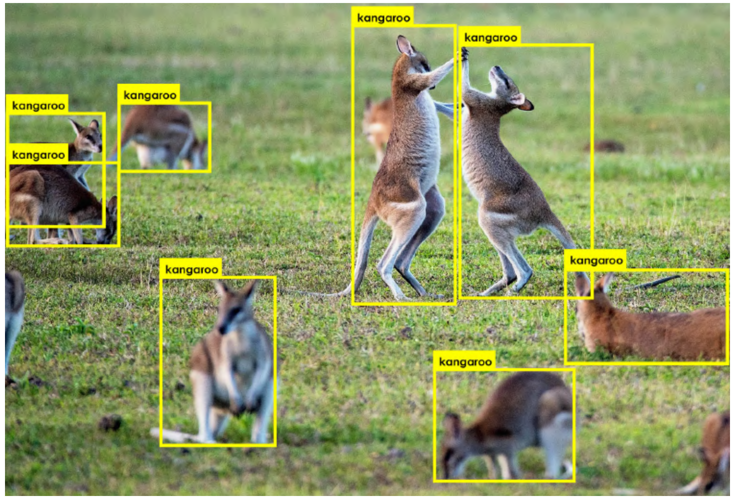
Jingzong Li, Libin Liu, Hong Xu *, Shudeng Wu, Chun Jason Xue

香港城市大學
City University of Hong Kong

中关村实验室
ZGC Lab

香港中文大學
The Chinese University of Hong Kong

Video analytics become more and more pervasive



Wild-life camera
Learn about the habit of animals

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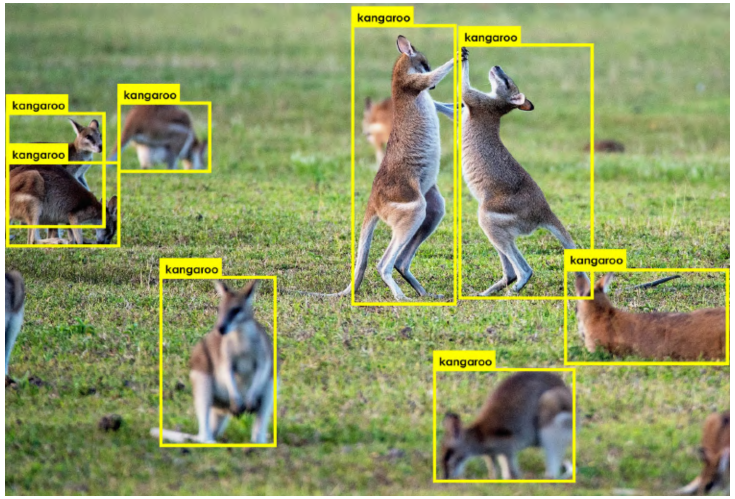

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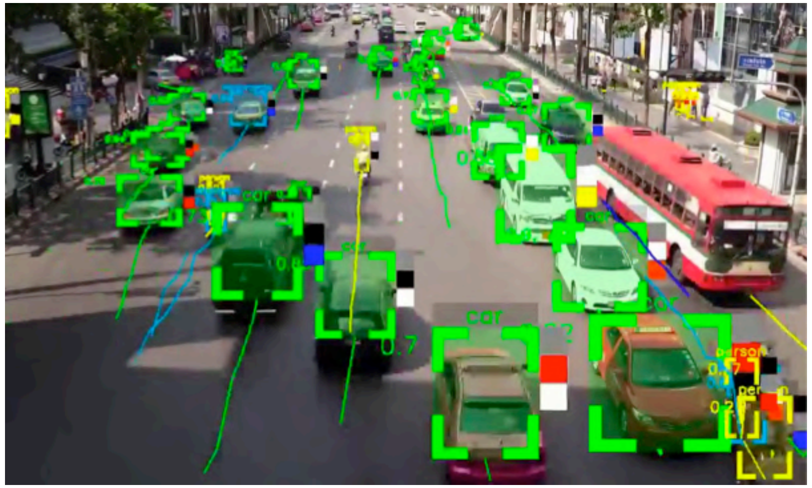

Traffic camera
Monitor the traffic condition

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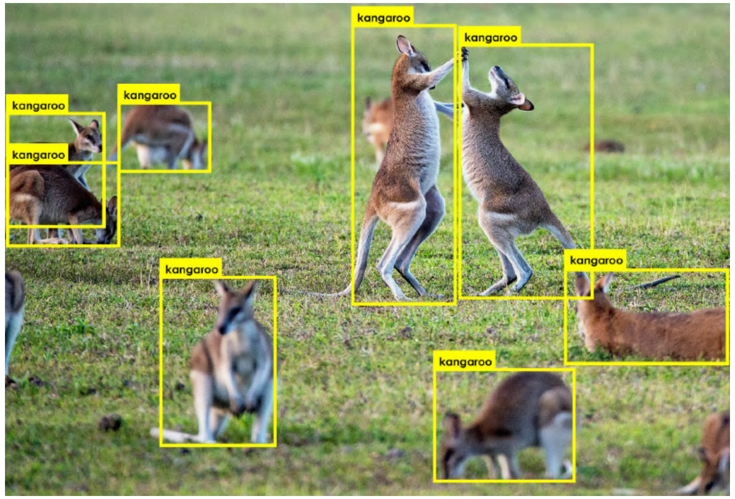

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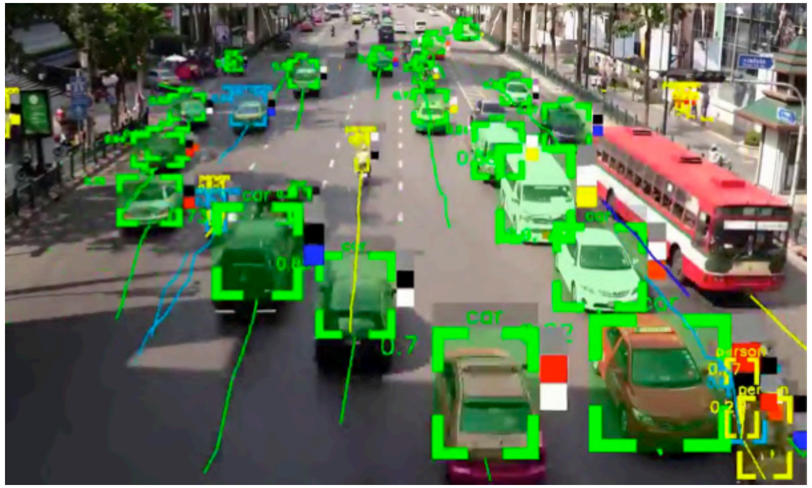

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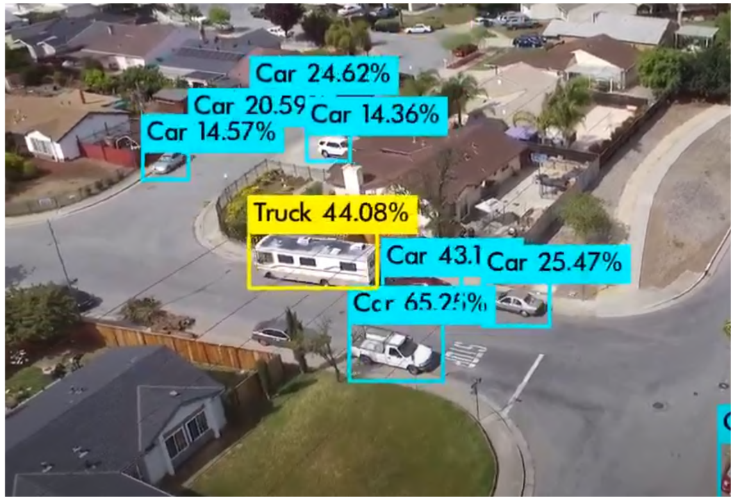


Drone camera
Detect the suspect vehicles

Video analytics on ~~cloud~~ edge era

Computation is shifted to the edge:

- Emergence of smart cameras;
- Unreliable and limited upload bandwidth;
- Privacy reason.

DNNCam™ AI camera

Challenges of video analytics on edge devices

Resource on edge devices is constrained.

VIEW TECHNICAL SPECIFICATIONS >

GPU	128-core Maxwell
CPU	Quad-core ARM A57 @ 1.43 GHz
Memory	4 GB 64-bit LPDDR4 25.6 GB/s

NVIDIA Jetson Nano

Challenges of video analytics on edge devices

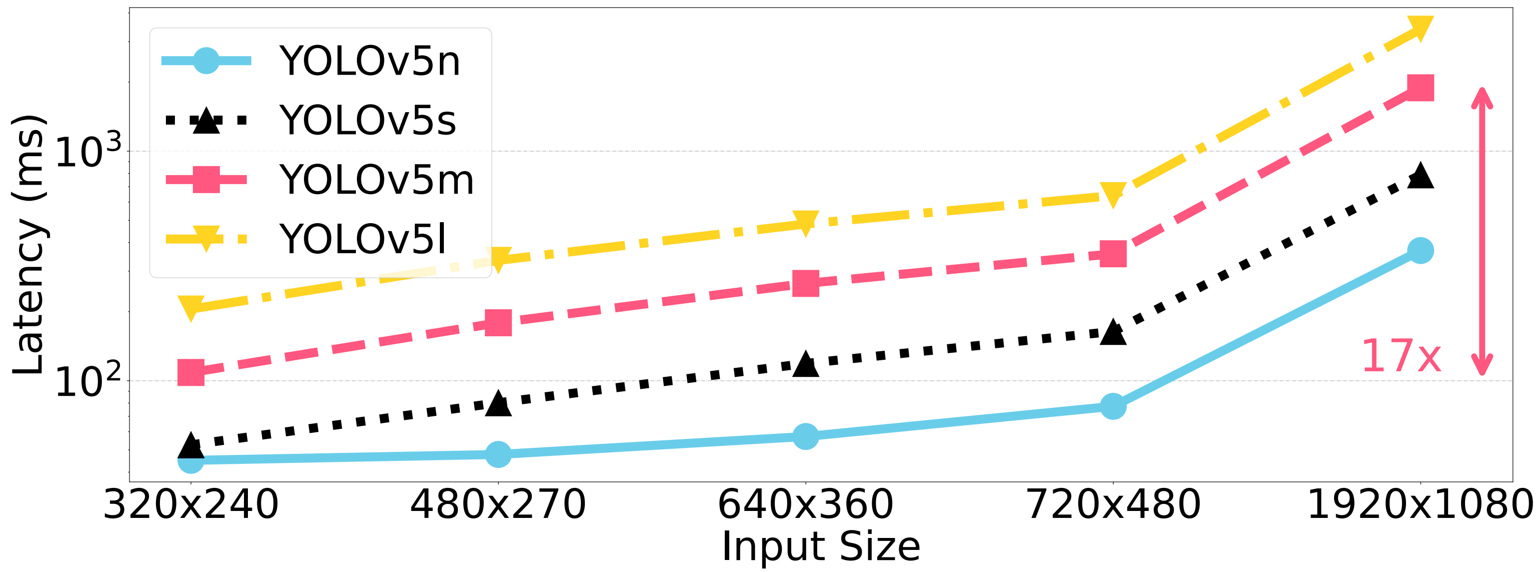
Resource on edge devices is constrained.

Vison-based DNNs are compute-intensive.

Model:
- YOLOv5

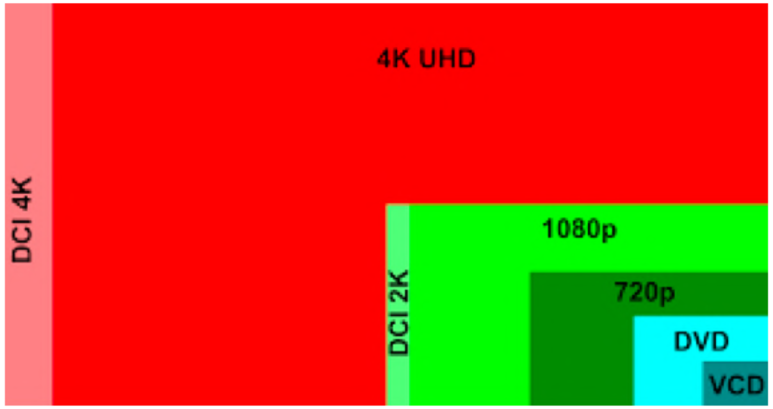
Device:
- Jetson Nano GPU

Dataset:
- NVIDIA AI City Challenge (AICC)



Challenges of video analytics on edge devices

- Resource on edge devices is constrained.
- Vison-based DNNs are compute-intensive.
- Ever-increasing video resolution of cameras.



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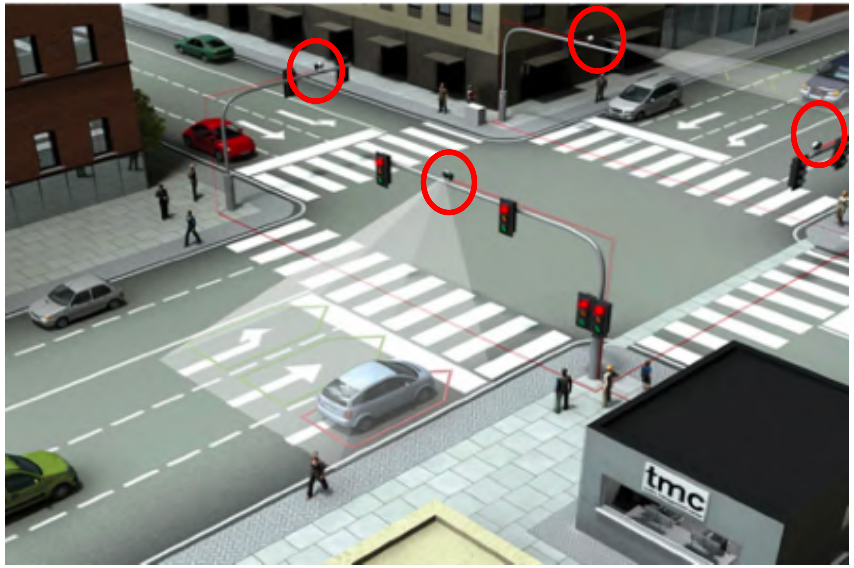
Ever-increasing video resolution of cameras.

Compute cost grows with number of cameras.



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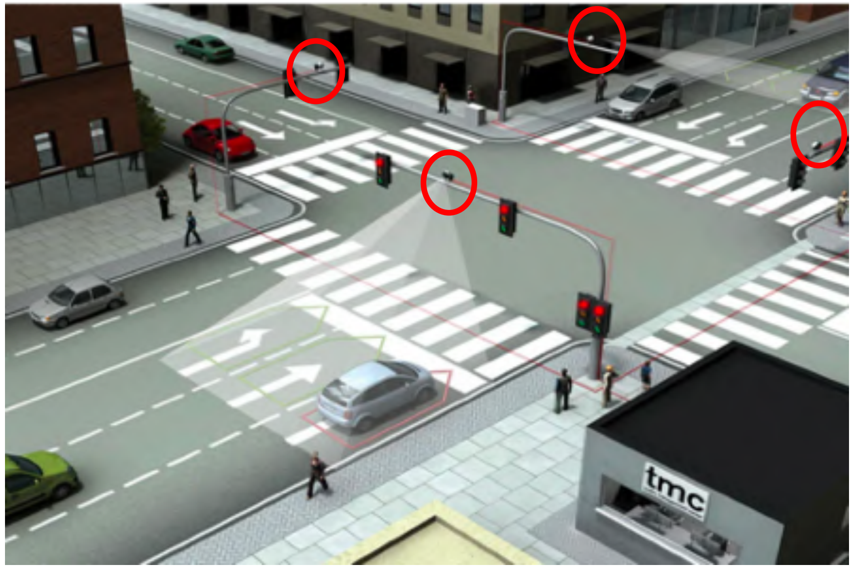

Resource-efficient inference is needed on constrained edge devices

Overlapping field-of-views (FoVs) across cameras

Cam. 1

Cam. 2

Cam. 3

Cam. 4

Observation: large overlapping FoVs

Source: NVIDIA AI City Challenge (AICC)

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Redundant inference work!

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Can they share inference results between each other?

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Overlapping field-of-views (FoVs) across cameras

Cam. 1

Cam. 2

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Cam. 4

Observation: large overlapping FoVs

↓

Redundant inference work!

↓

Can they share inference results between each other?

↓

Only need to run DNNs on pixels that are beyond Overlapping FoVs

Source: NVIDIA AI City Challenge (AICC)

We propose Polly to achieve inference sharing

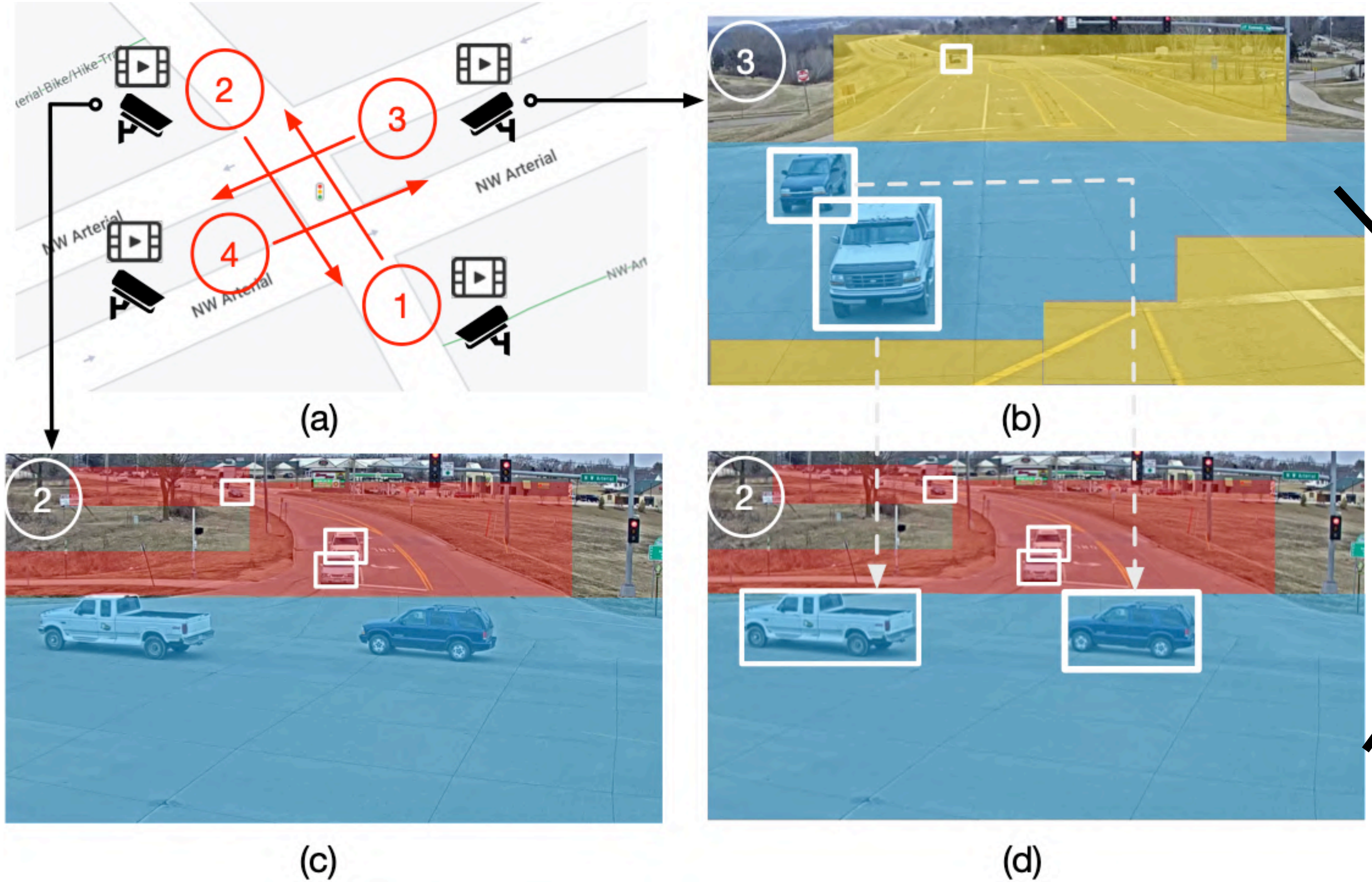

Illustration of inference sharing

Take camera 2 and camera 3 as example

Blue zones are overlapping FoVs

DNN model only needs to run on the unique patches (red).

Challenges to achieve inference sharing

- How to identify the overlapping FoVs **automatically**?
- How to share or transfer the inference results across cameras **effectively**, so that the overall inference accuracy loss is **minimal**?

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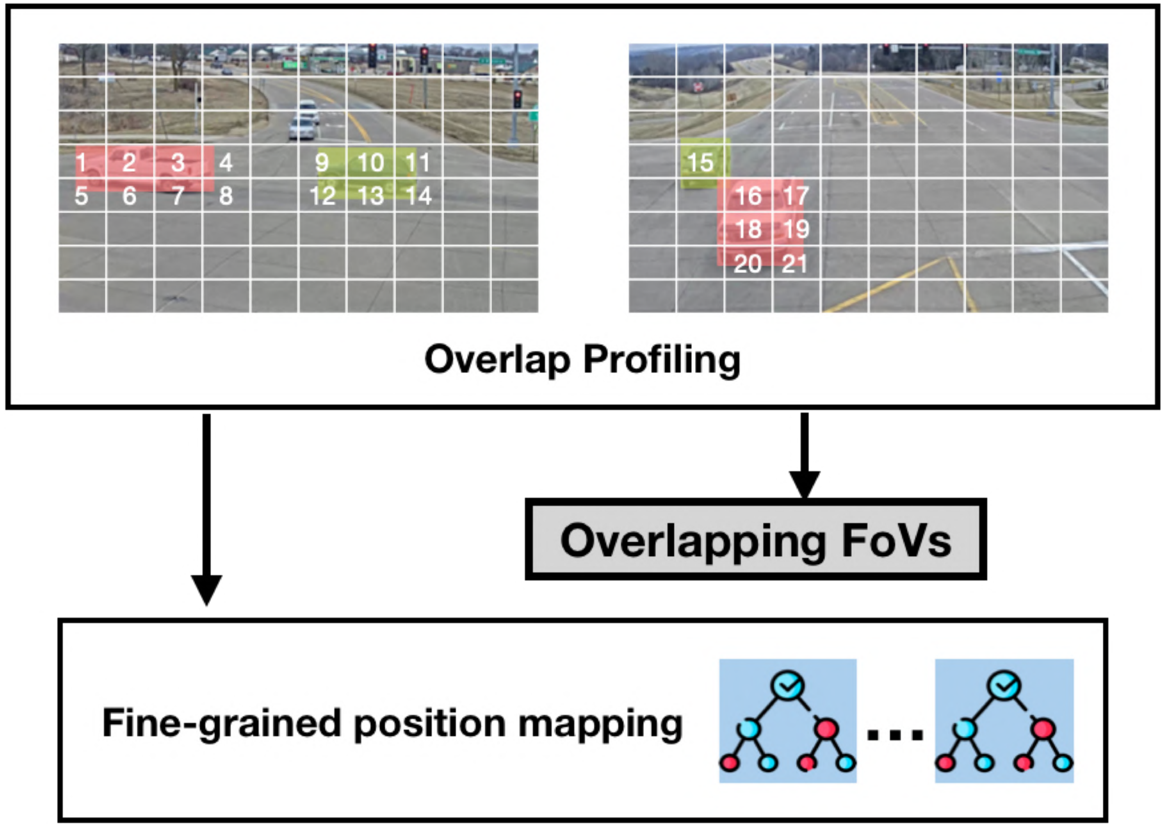
- Offline phase
- Online phase

Polly System Overview

Server (Offline Phase)

Edge Device (Online Phase)

Polly System Overview



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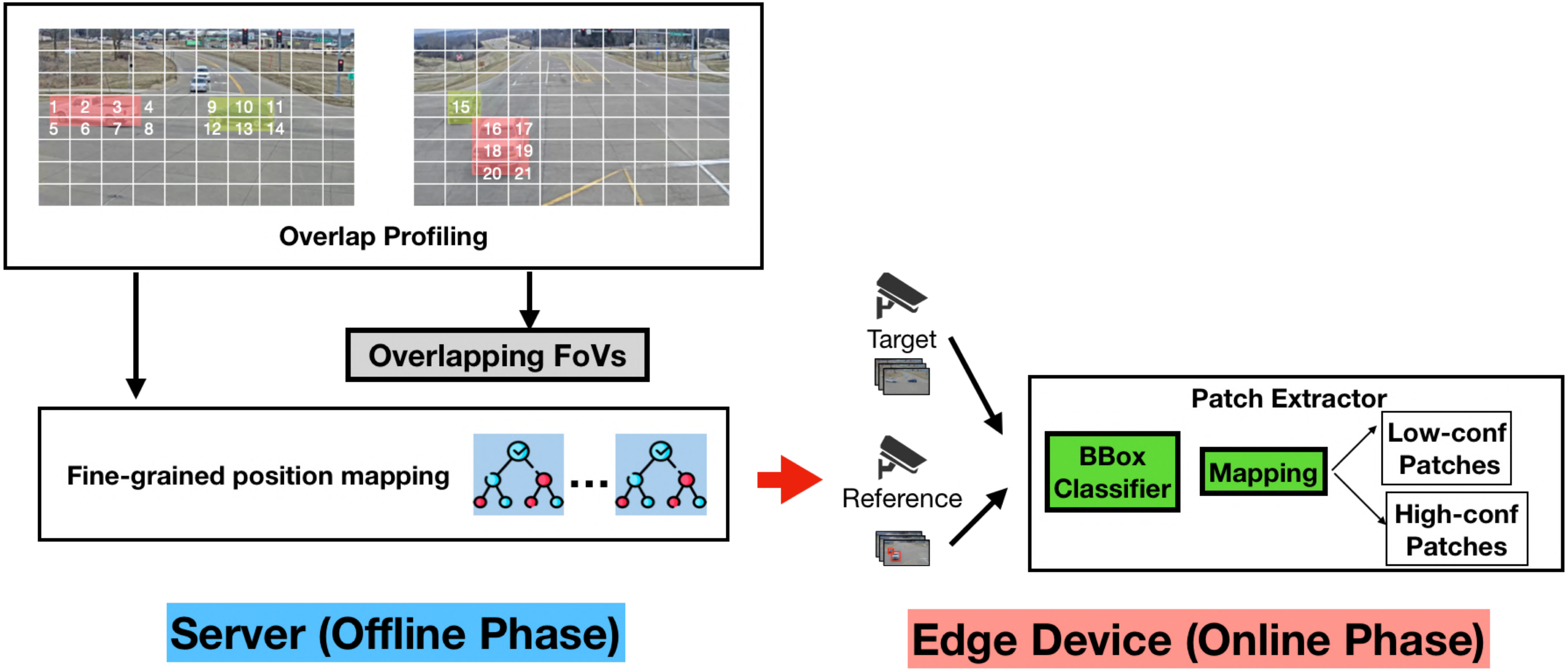

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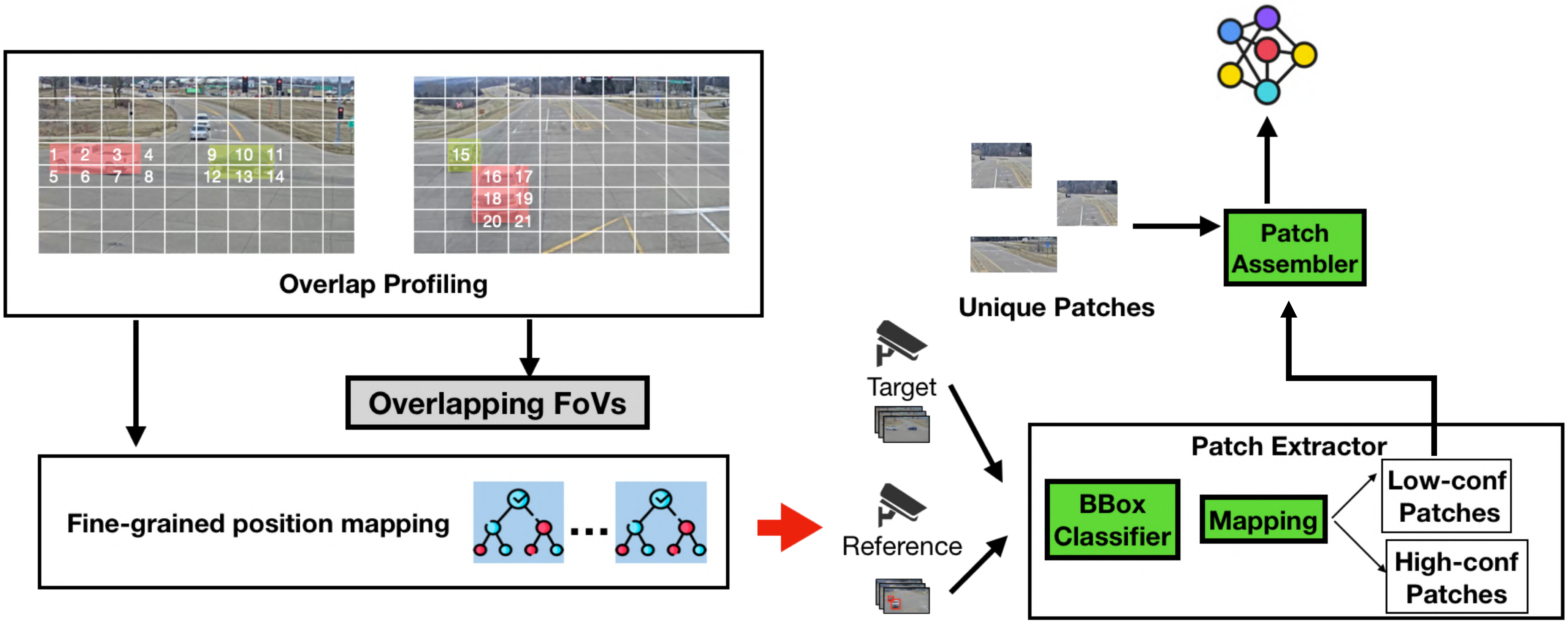

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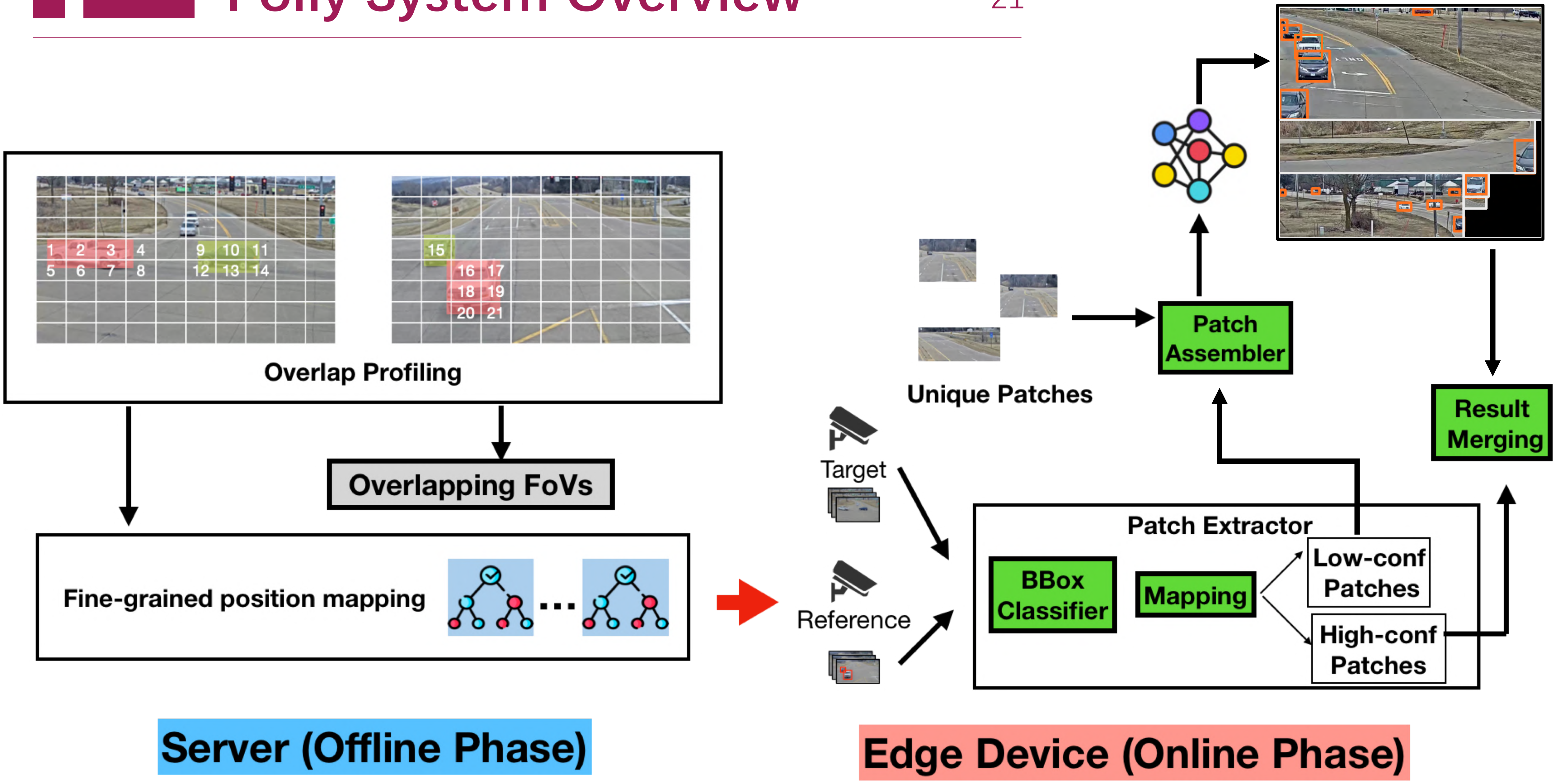
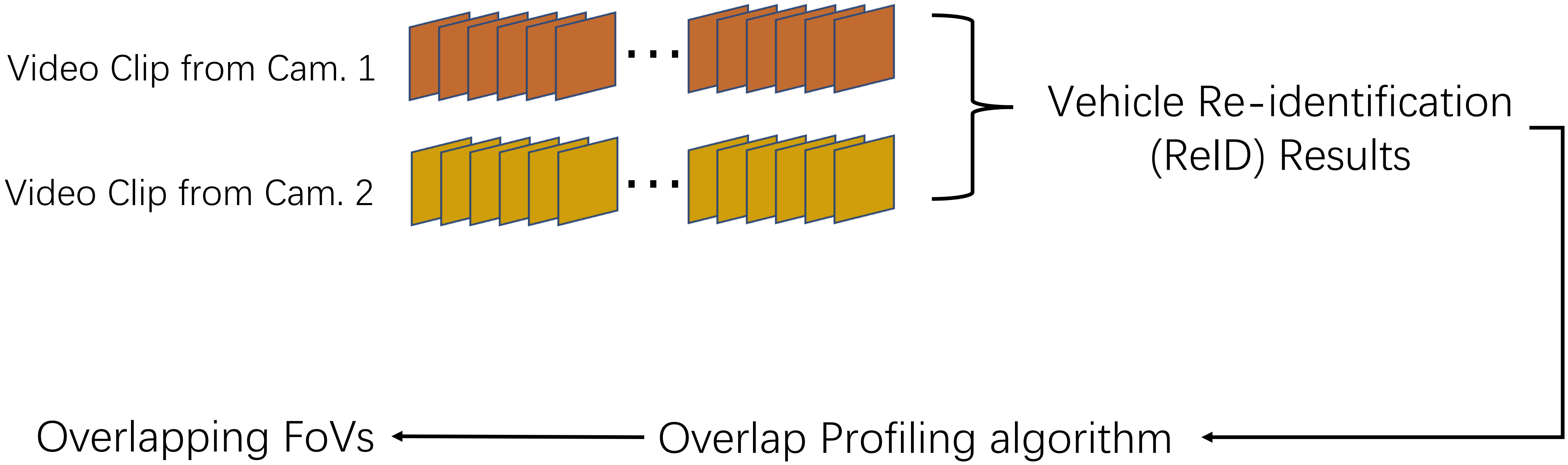


Offline Phase - Overlap Profiling Algorithm

Rationale: The algorithm utilizes the positions of the same vehicle in different cameras to profile the overlapping FoVs automatically between them.



Offline Phase - Overlap Profiling Algorithm

Example of overlap Profiling:

(a) Cam. 2 (b) Cam. 3

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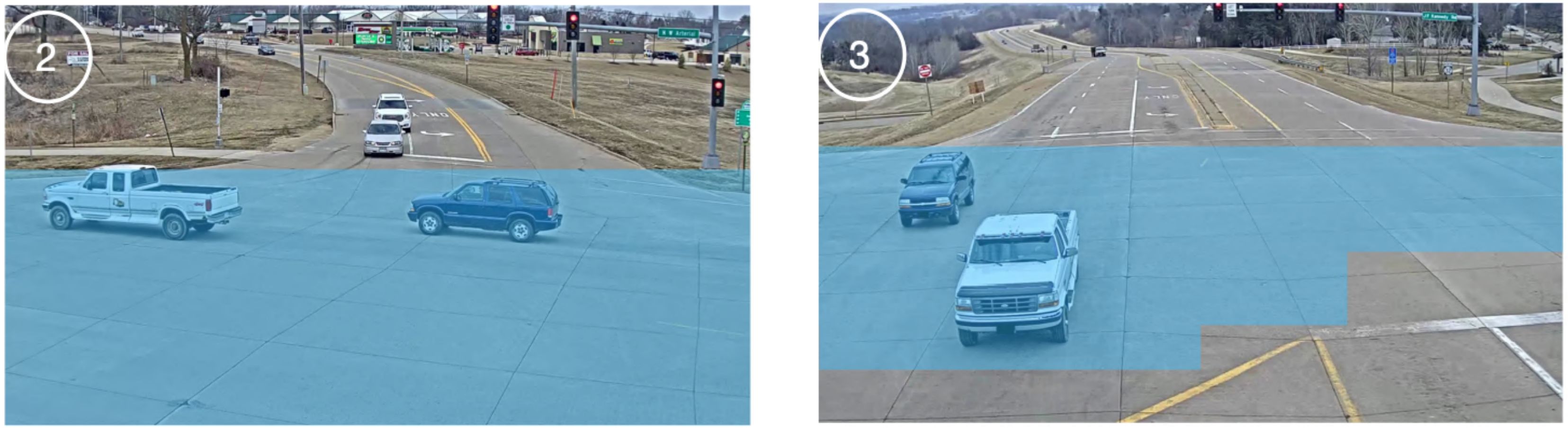
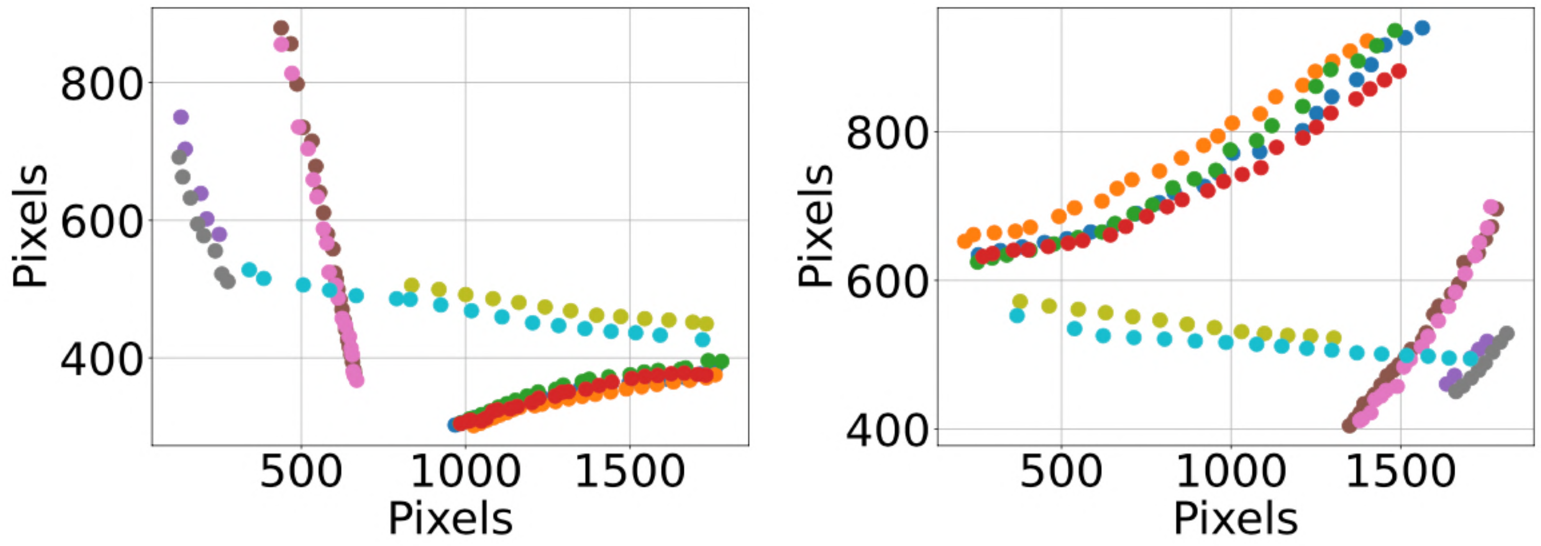
Overlapping FoVs:



Offline Phase - Fine-grained Position Mapping

Based on the overlapping FoVs from the profiling algorithm, Polly can further build a fine-grained position mapping for effective inference sharing.



Trajectories of randomly selected vehicles from two cameras. Dots with the same color represent the centroids of the same vehicle.

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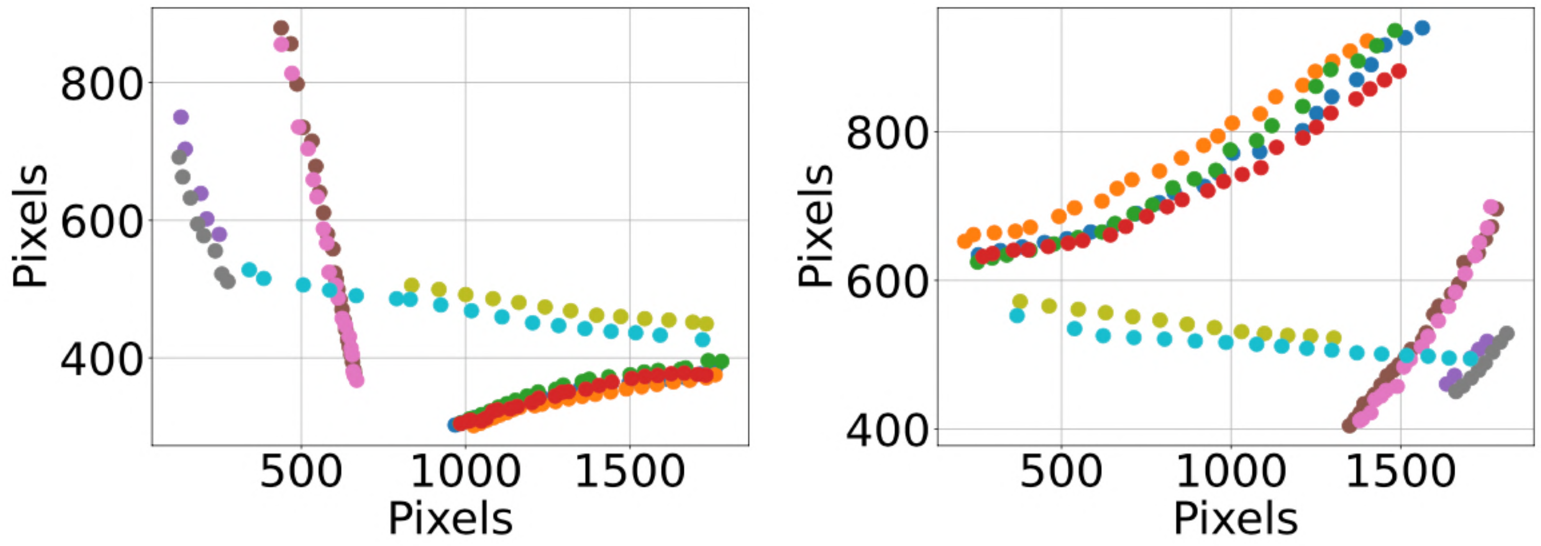


Trajectories of randomly selected vehicles from two cameras. Dots with the same color represent the centroids of the same vehicle.

We can see that vehicles with **similar trajectories** in one camera appear in the other one with also very **similar trajectories**.

Offline Phase - Fine-grained Position Mapping

Position Mapping:
- Input: [x, y, l]
- Ouput: [x', y', l']

Compare two approaches:
- Black-box: MLP (64-64-3)
- White-box: Regression Tree

Data augmentation:
- Enrich training samples
- Enhance mapping accuracy

Method	R^2	Training Time (s)	Inference Time (ms)
MLP	0.950	631	0.38
Multi-output Regression Tree	0.996	5	0.27

TABLE III: Performance of different mapping methods

Offline Phase – Other design

grass fields, bushes and houses

- **Background removal**: running vehicle detection on the background areas where vehicles do not exist at all is a waste of resource,

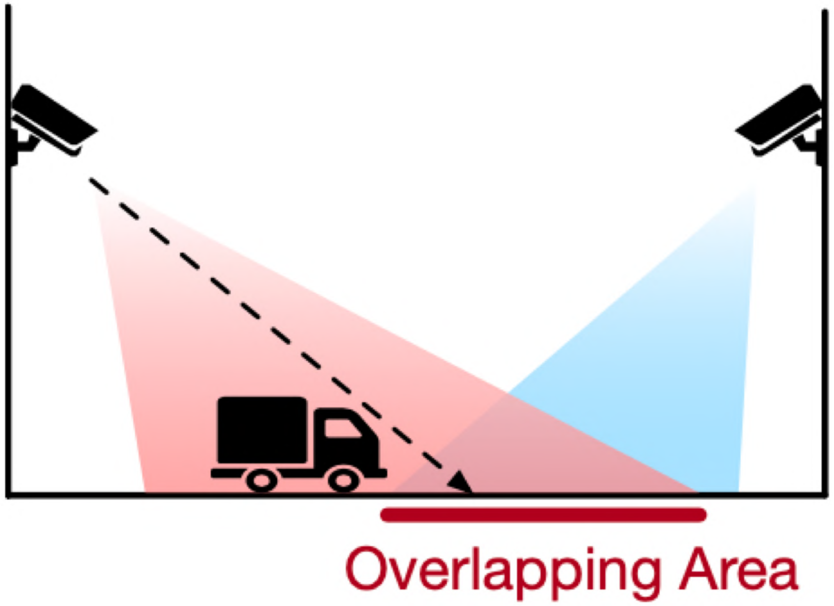
- **Reference camera selection**: we select the camera that has the largest average overlapping FoVs with the remaining ones as the reference camera.

Please refer to the paper for more details.

Online Phase – Perspective Effect

Directly mapping the detected vehicles from the reference camera to the target camera can lead to **erroneous results** due to the low quality of shared inference result.

One main cause is the **perspective effect**.

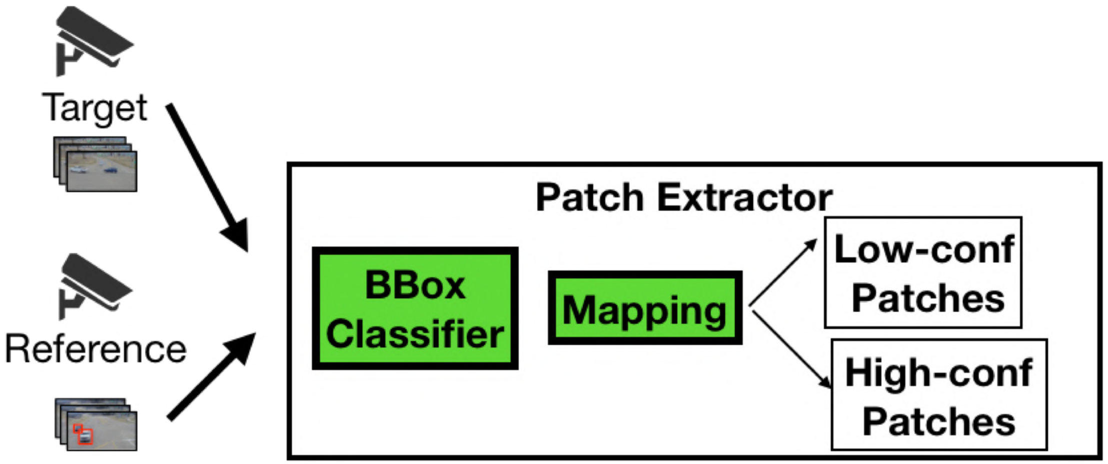


An illustration of the perspective effect.

Online Phase – Patch Extractor

Problem: some parts of the reference camera's frame has low sharing quality.

Solution: just run the DNN model on the corresponding parts of the frame in the target camera. We design the **patch extractor** to identify the low-confidence parts and extract them.

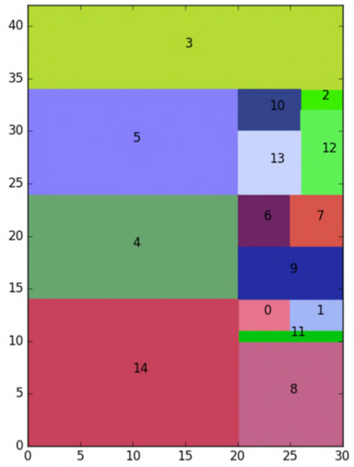


Besides low-confidence patches, the target camera's **unique FoVs** are also extracted.

Online Phase – Patch Assembler

Problem: Both the low-confidence and unique patches need to be processed by the DNN for object detection, and running the model on each patch individually is inefficient.

Solution: we design the **patch assembler** to tile these patches into a minimized rectangle so as to reduce inference latency (e.g. 1888ms for 1920×1080 full frame, 265ms for a 640×360 tiled rectangle).

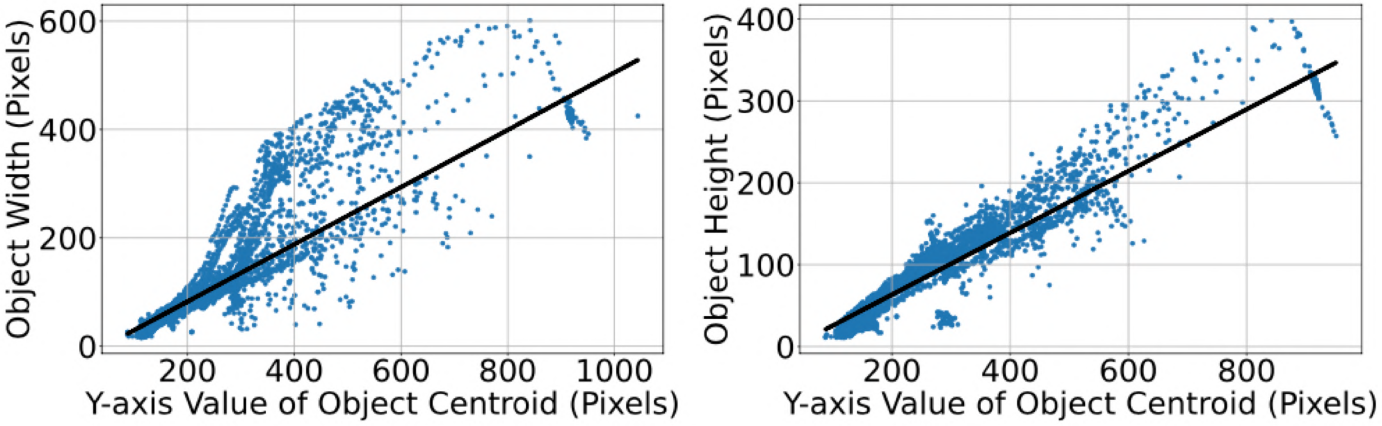


2D Bin packing problem:

- NP-hard
- Fix the width of the bin
- Guillotine bin packing algorithm

Online Phase – Patch Assembler

Observation: the object size is roughly linearly relative to the Y coordinate of the object's centroid.



(a) Y-axis value vs. width. (b) Y-axis value vs. height.

Fig. 8: Y-axis value of object centroid versus object size.

Optimization: apply down-sample to certain patches.

Online Phase – Patch Assembler

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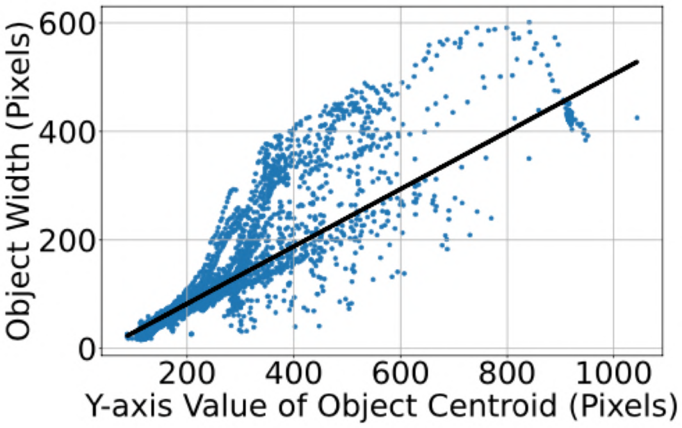
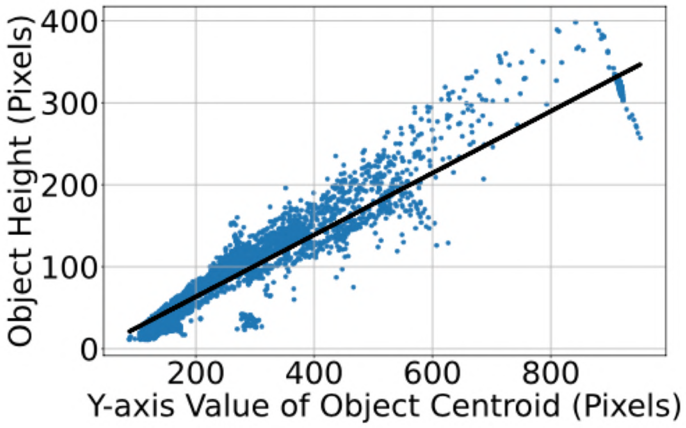


(a) Y-axis value vs. width.



(b) Y-axis value vs. height.

Fig. 8: Y-axis value of object centroid versus object size.

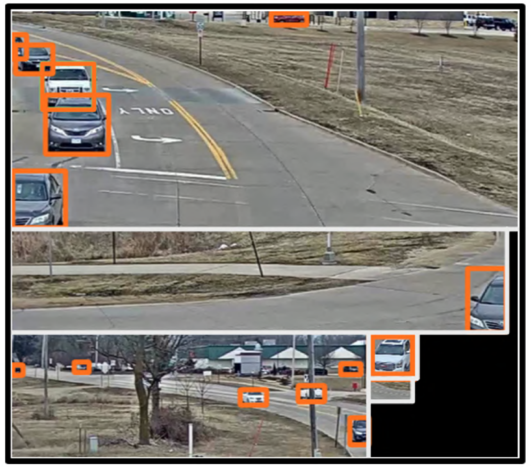
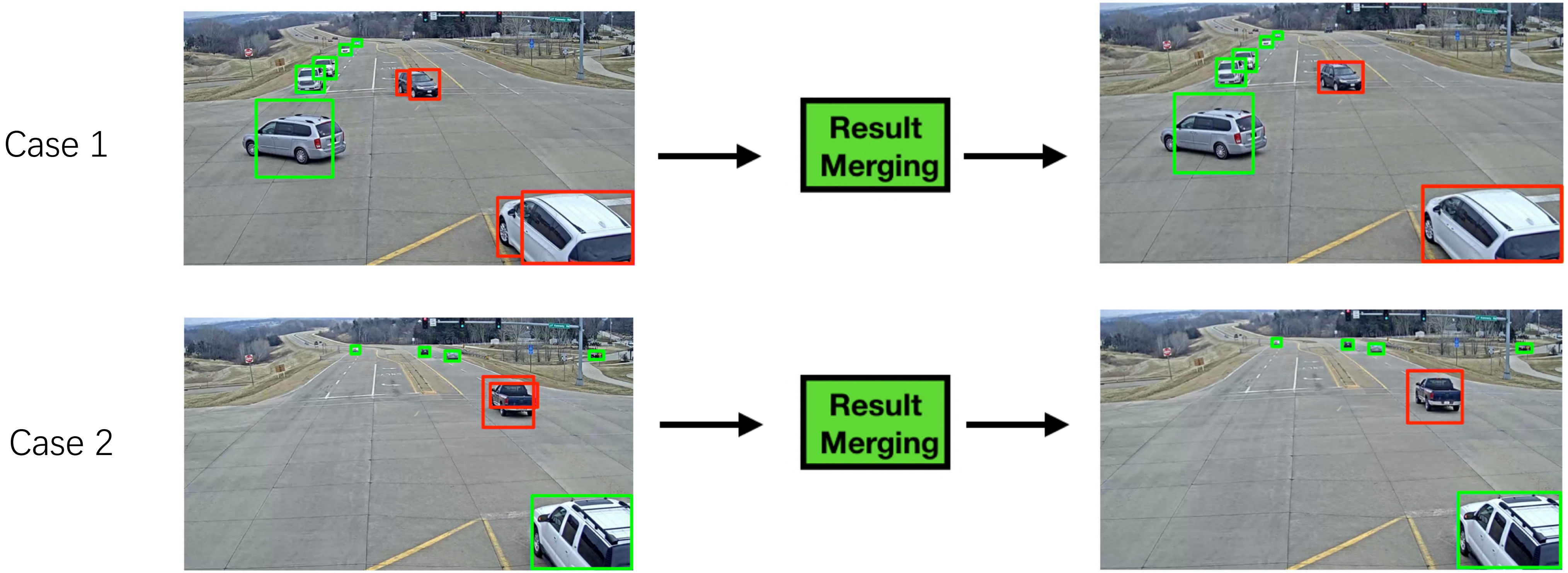


Fig. 9: An example of the tiled rectangle with detection results.

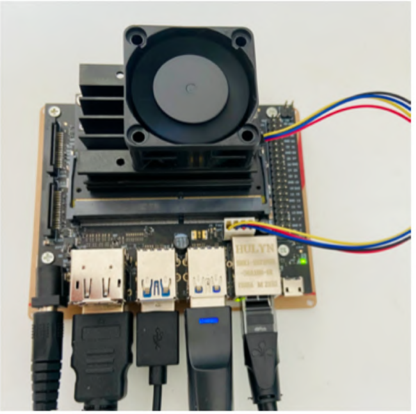
Optimization: apply down-sample to certain patches.

Online Phase – Result Merging

At the last step, Polly needs to combine the inference results from the two pipelines, i.e., **inference sharing** from the reference camera, and **direct inference** of the titled image.



Evaluation – Experiment Settings



Testbed: We run our experiments on Jetson Nano, a commonly used edge device equipped with one 128-core NVIDIA Maxwell GPU.

Dataset: NVIDIA AI City Challenge (AICC) [1]

Detection Models: YOLOv5 variants with different sizes

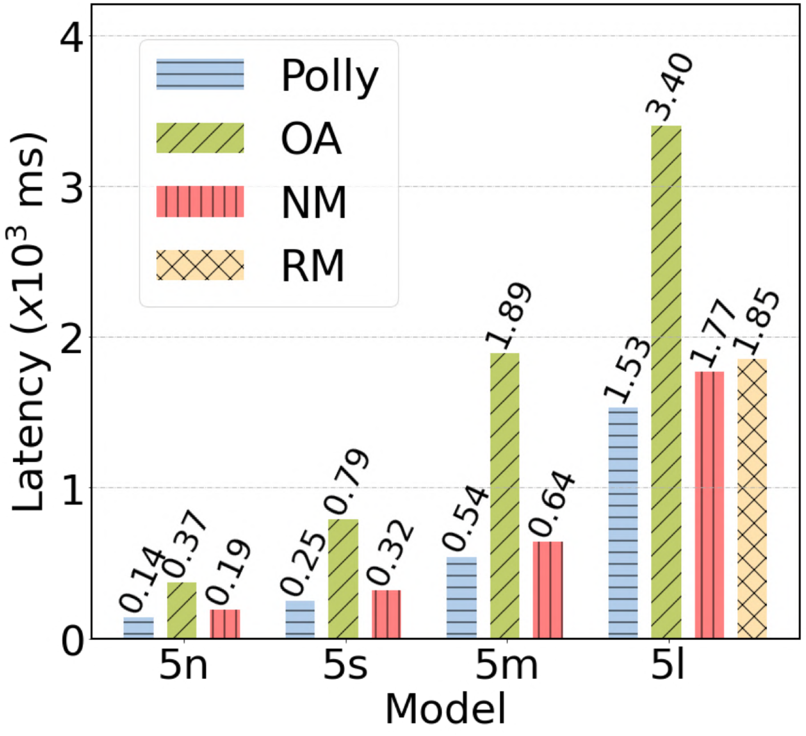
Baselines:
- Overlapping-Agnostic (OA)
- Naive-Merging (NM)
- Remix-Mimic (RM)

Metrics:
- End-to-end latency
- Detection Accuracy (F1)

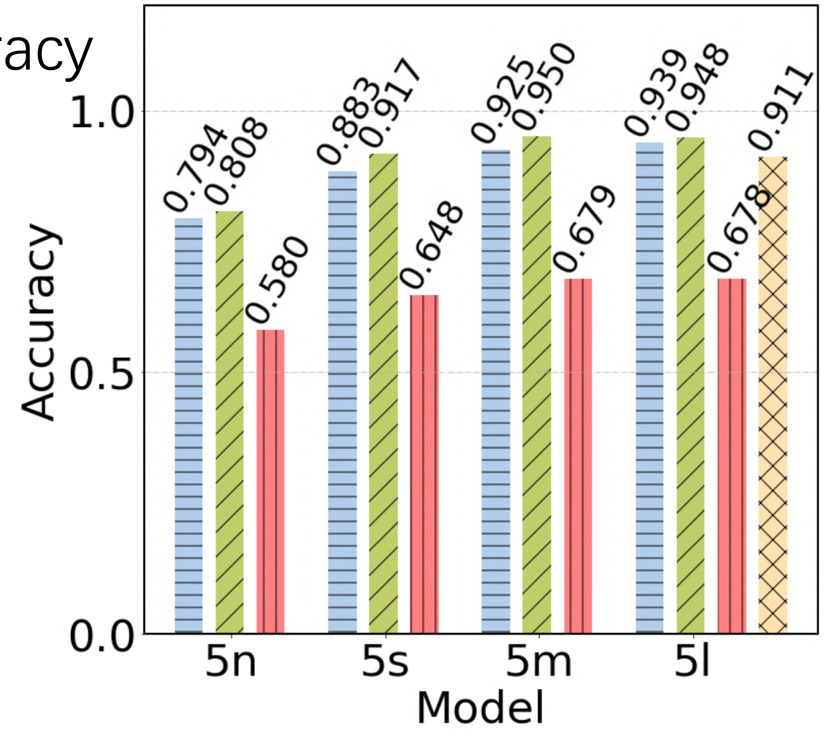
[1] 2022 NVIDIA AI City Challenge. https://www.aicitychallenge.org/.

Evaluation – Overall Performance

Latency



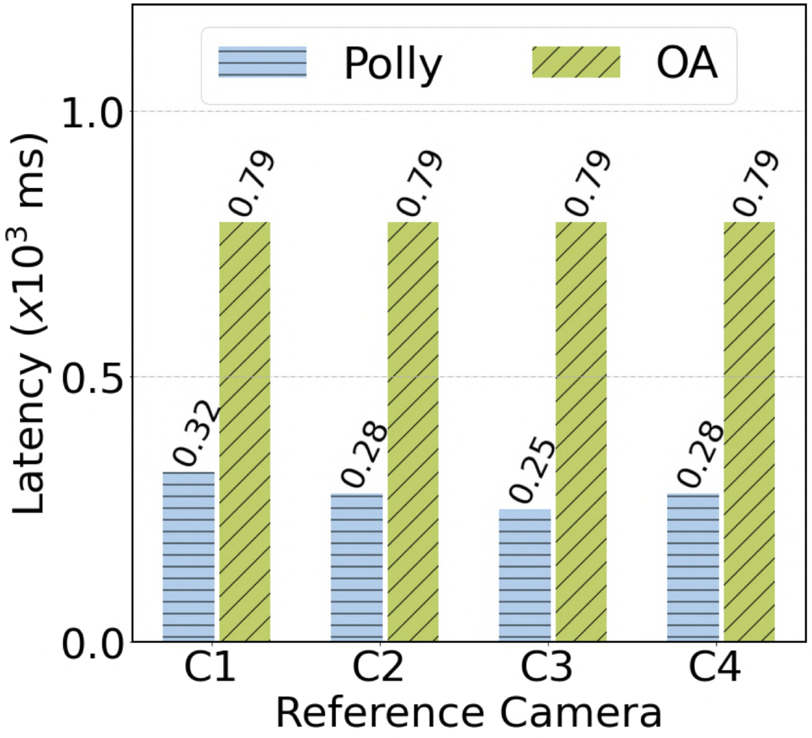
Accuracy

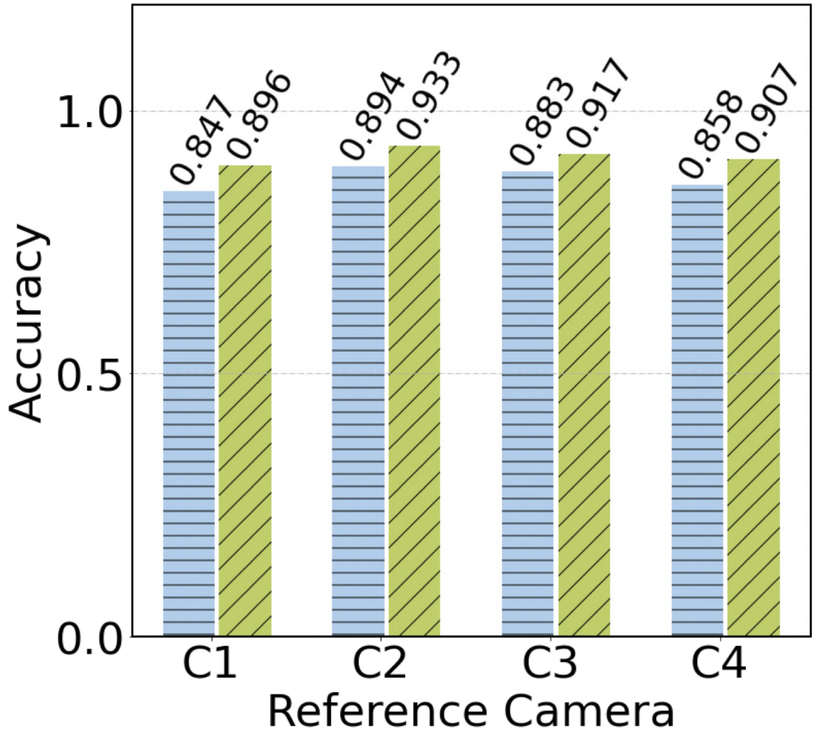


- Polly **outperforms** all baselines.
- Compared with OA, Polly's overall latency reductions range from 55% to 71%.

- Polly's accuracy is almost **on par with** OA, with at most 3.7% loss.
- Polly can achieve better accuracy while reducing latency by **70%** compared to RM.

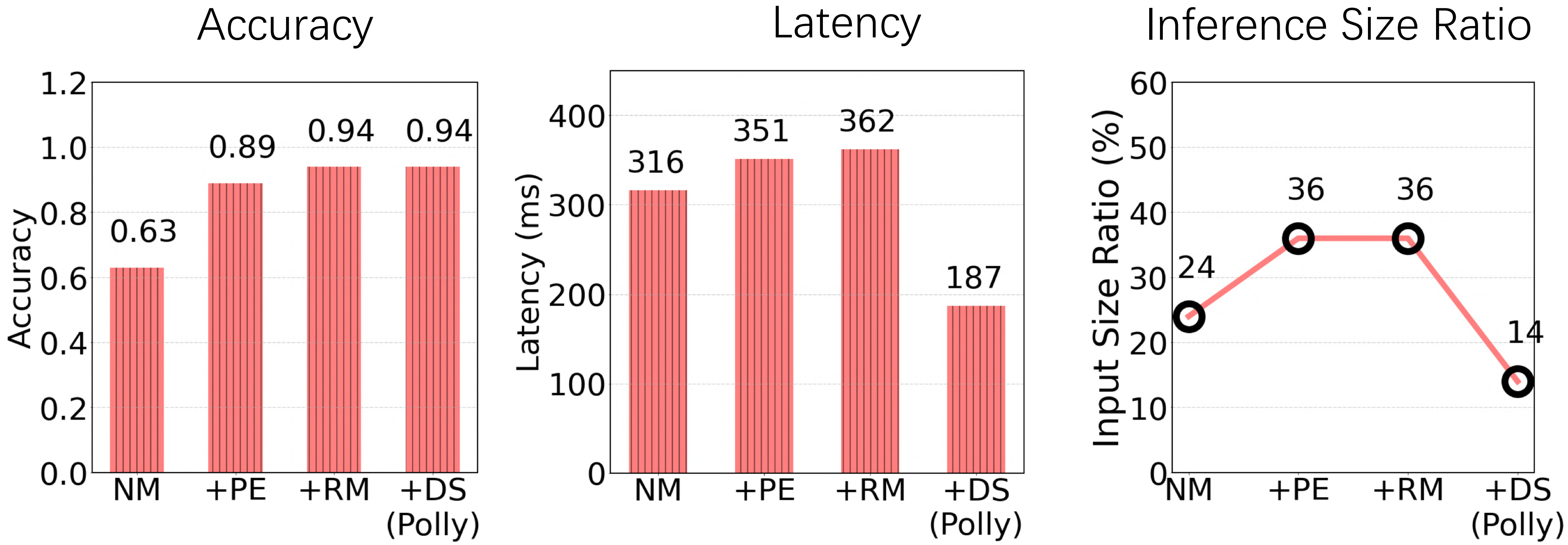
Evaluation – Impact of Reference Camera Selection





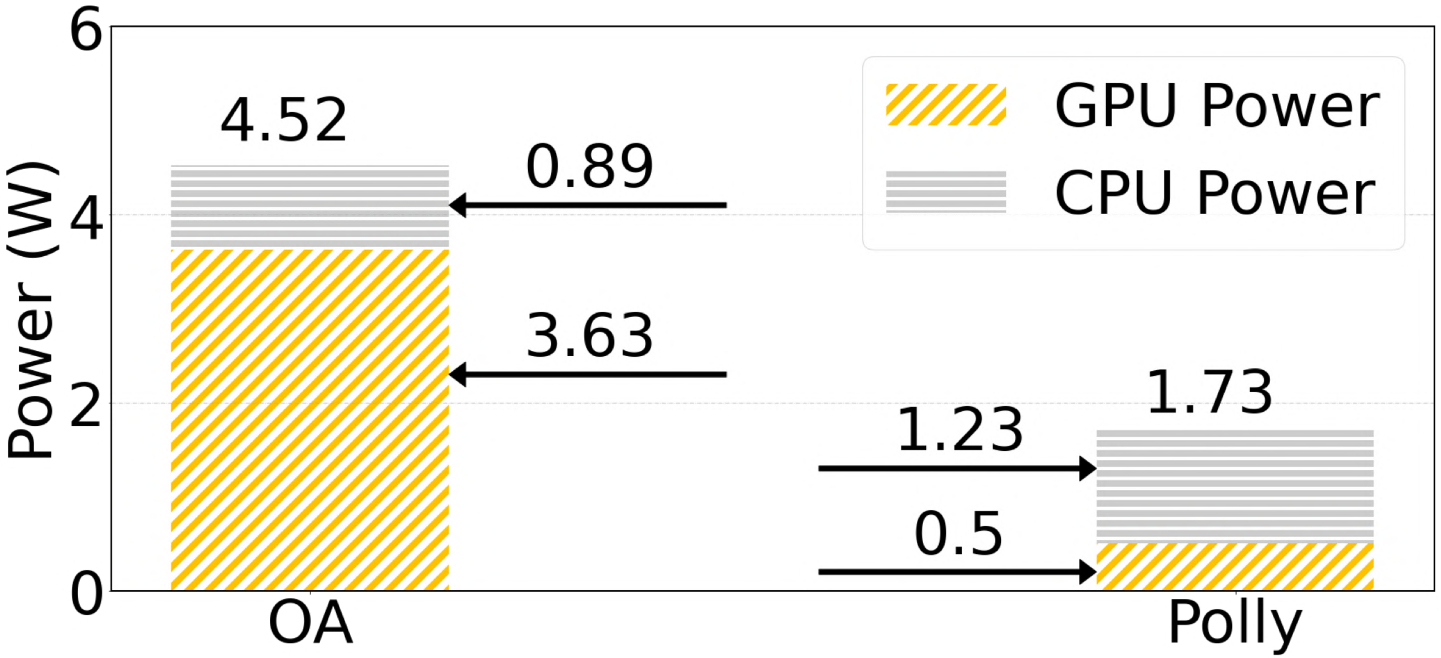
- Inference sharing is **consistently** effective with different cameras selected as the reference.

Evaluation – Performance Breakdown



- PE brings **considerable** accuracy gain.
- DS improves the latency by 48 % **without** accuracy loss.

Evaluation – Energy Consumption



Polly saves 61.73% power in total against OA:

- 86.23% GPU power reduction
- Slightly more CPU consumption

Conclusion

- **Problem**: In the cross-camera scenario, video analytics tasks pose severe burden for resource-constrained edge devices.
- **Our contribution**: Polly, the **first** full-fledged video analytics system to achieve inference sharing.
- **Results**: Polly achieves significant latency reduction almost without impairing accuracy.

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Thank you

{ jingzong.li@my.cityu.edu.hk }