

Turbo: Opportunistic Enhancement for Edge Video Analytics

Yan Lu, Shiqi Jiang, Ting Cao, Yuanchao Shu

SenSys 2022



NYU



Microsoft

Outline

- ❑ **Background of edge video analytics**
- ❑ **Opportunities for existing VAPs**
 - ❑ Idle computing resources
 - ❑ Hard samples
 - ❑ Image (Data) enhancement
- ❑ **Turbo**
 - ❑ Detector-specific GAN & Model-aware adversarial training
 - ❑ Resource-aware scheduler
- ❑ **Experiments**
- ❑ **Summary**

Video is everywhere

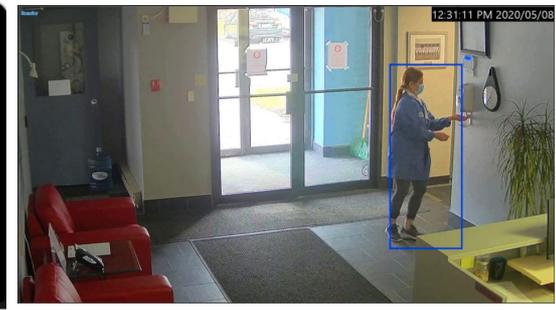


Sensors



Video Analytics

Diverse applications



Move to edge

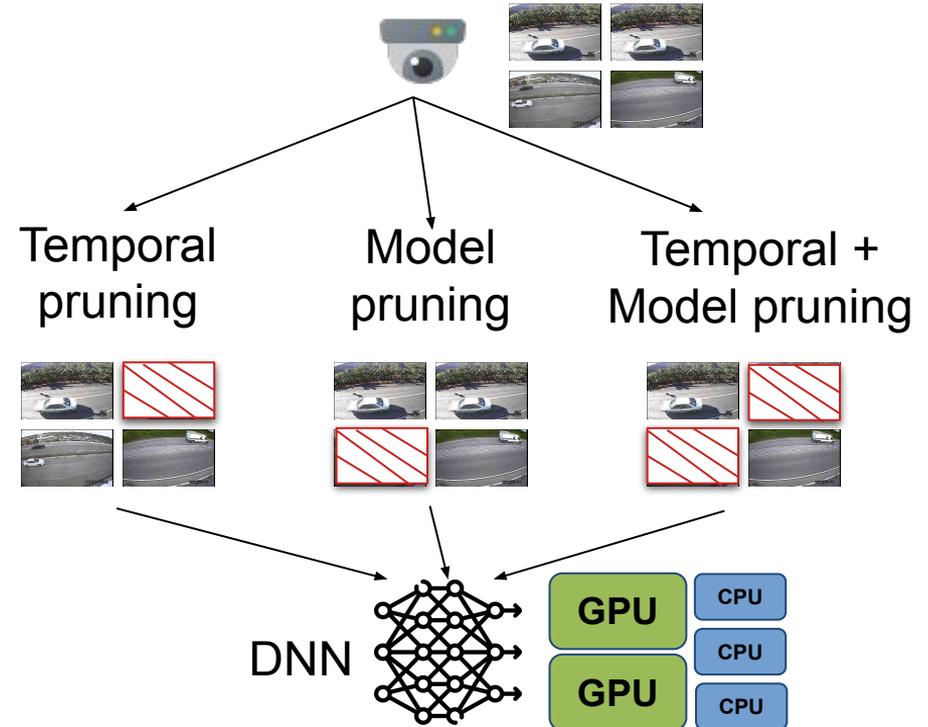


Privacy

Network

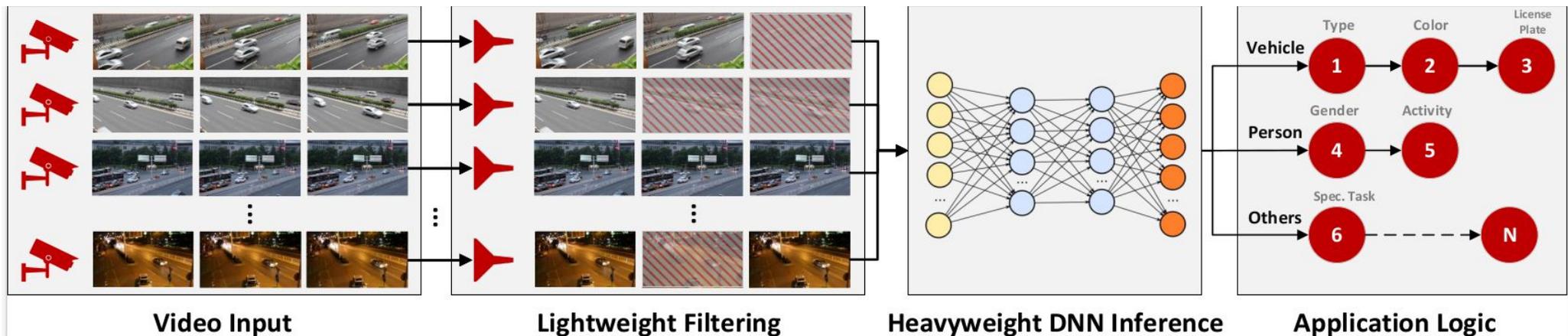


Edge Video Analytics Pipelines
(2015~2020)



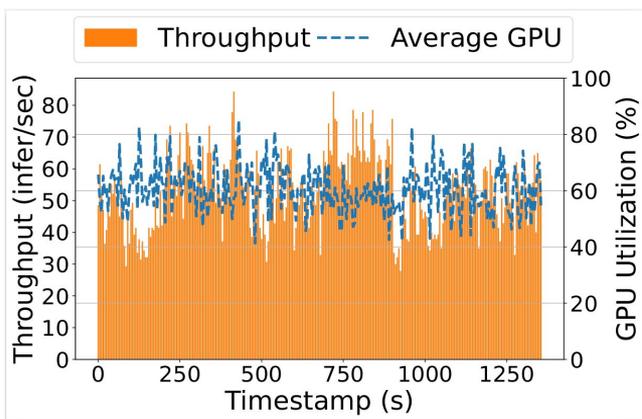
How many resources?
Usually, they are set to meet 4 fps instead of 2 or 3 fps!

Idle resources are common

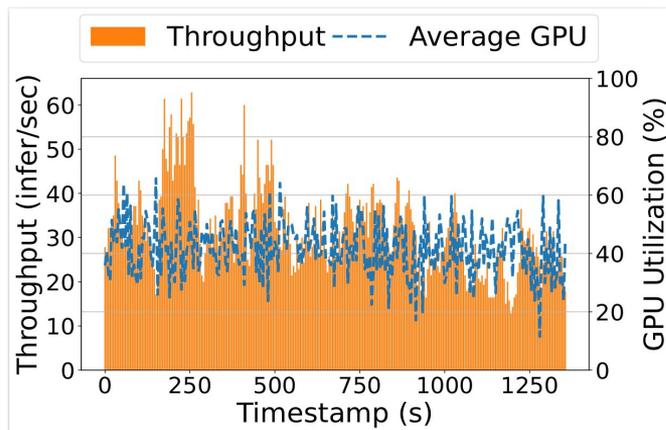


Can we **leverage** these idle resources to **improve** video analytics?

Idle resources are common



Vigil

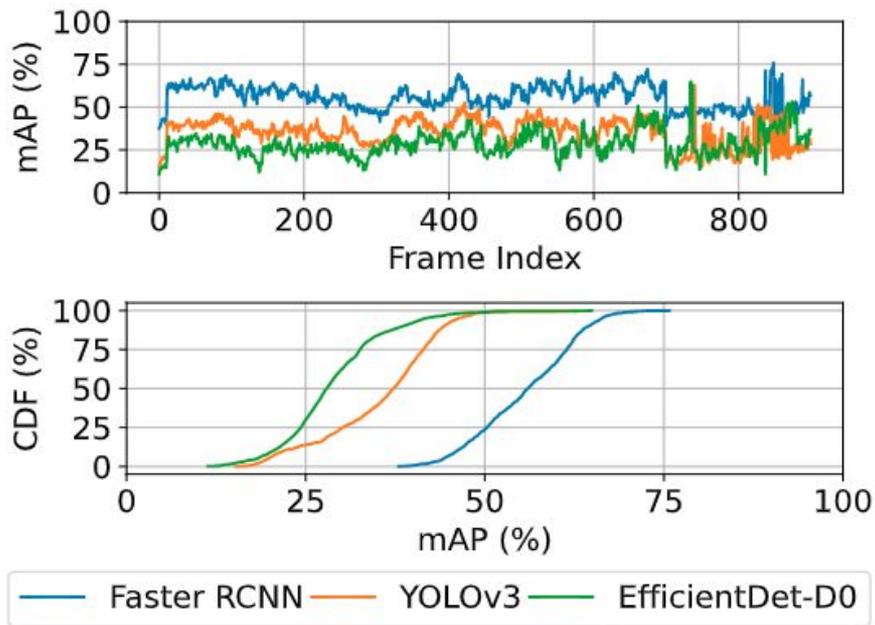


Glimpse

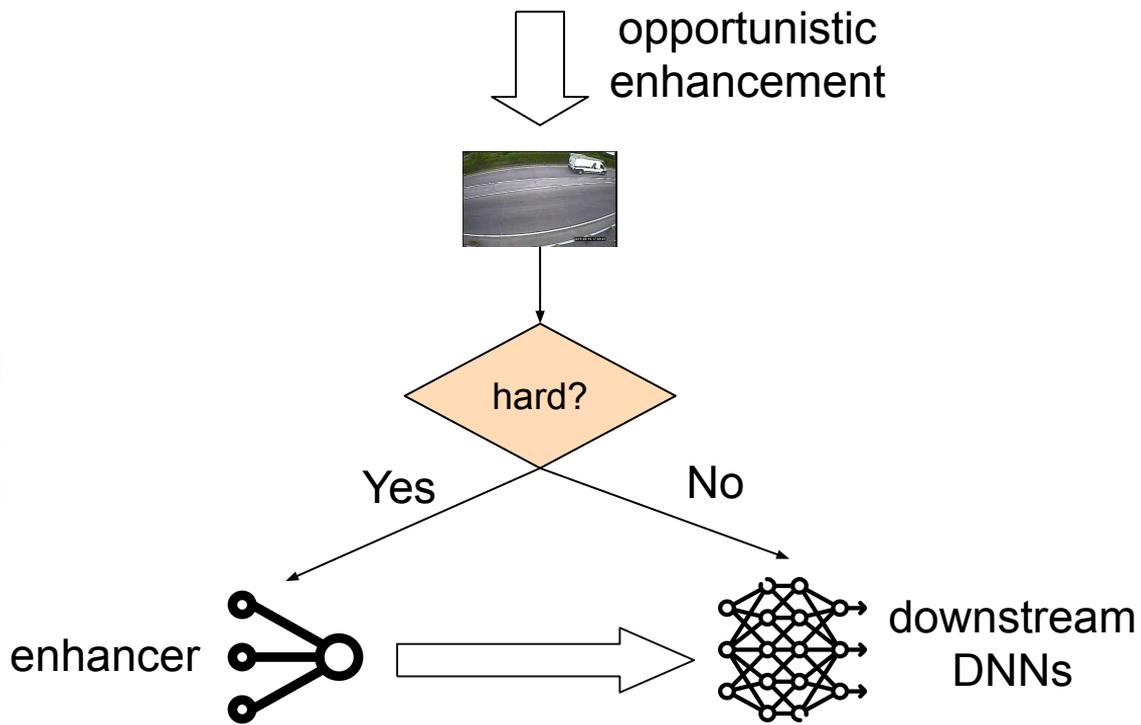
Vigil: 19.03% < 45 infer/sec
Glimpse: 7.26% > 50 infer/sec

It is hard because they are **non-deterministic** and **fragmented**!

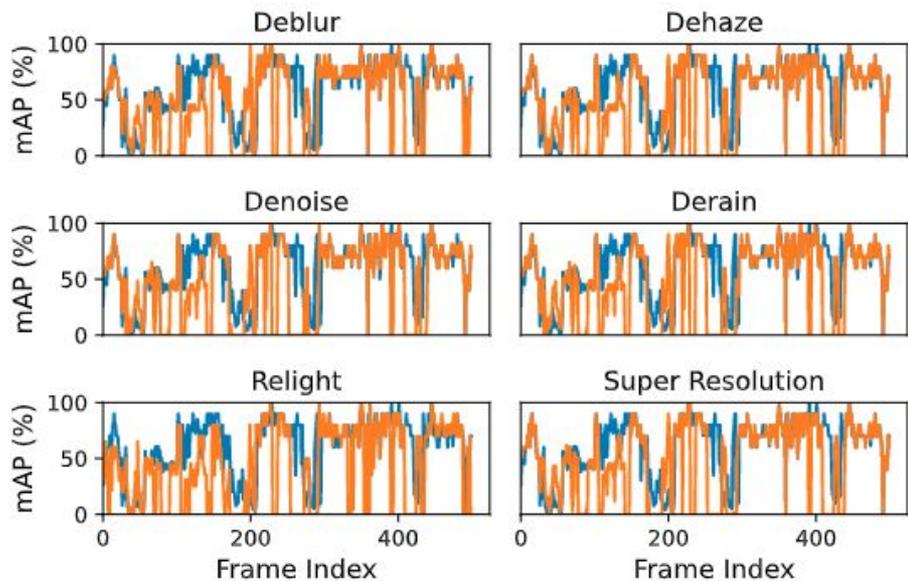
How to leverage idle resources?



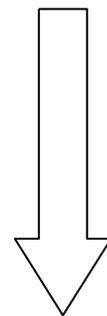
A **small portion** of frames make a bad overall mAP for detectors!



How to improve hard samples?



Off-the-shelf
image enhancement may help?



Why they
fail?

Human Visual Perception

≠

Downstream DNNs Accuracy

Key takeaways

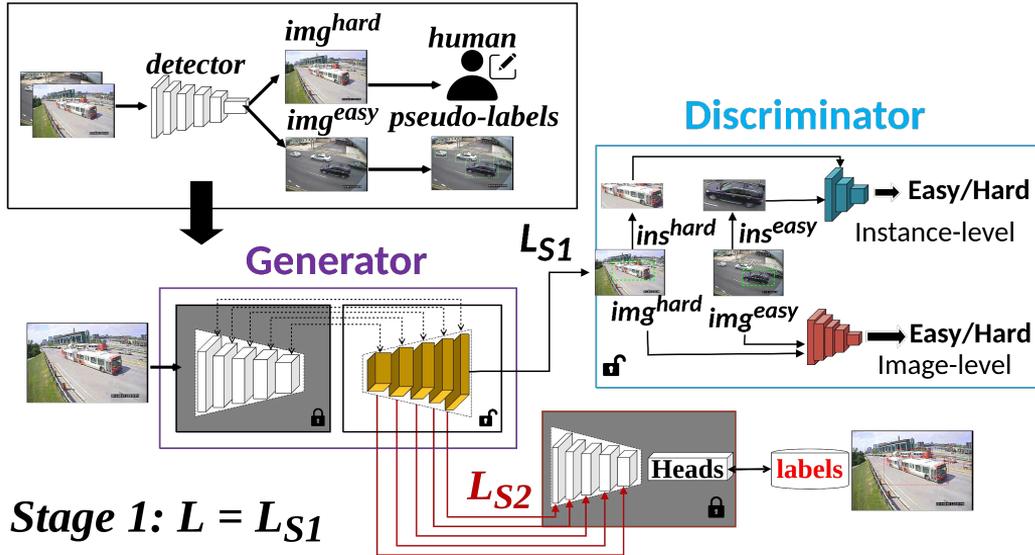
Idle computing resources are **common** but highly **dynamic** and **fragmented**.

A **small** portion of **hard** frames lead to a bad overall accuracy.

Running off-the-shelf opportunistic enhancement methods is **inappropriate**.

Model-aware Adversarial Training

Data preprocessing



Stage 1: $L = L_{S1}$

Stage 2: $L = L_{S2} + L_{S1}$ Object detection model

Stage 0: find easy/hard samples for a downstream detector.

Model-aware easy/hard

Stage 1: learning a $G(x)$ and $D(x)$ for a specific downstream object detection.

Hard \rightarrow Generator \rightarrow Easy

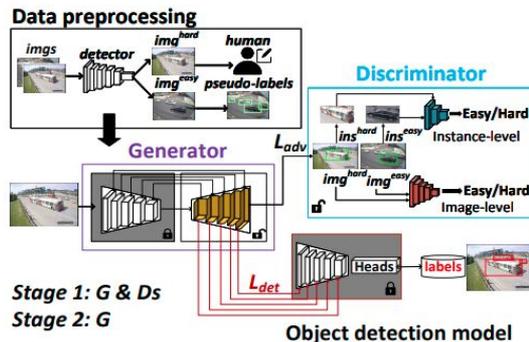
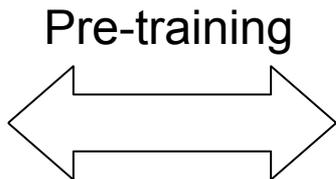
Stage 2: a multi-exit mechanism

Efficient Generator

Pre-training and fast adaptation



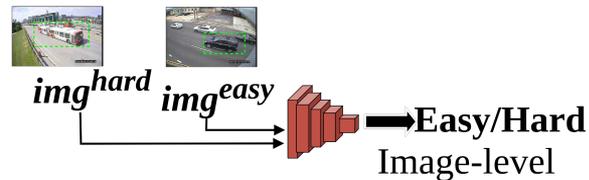
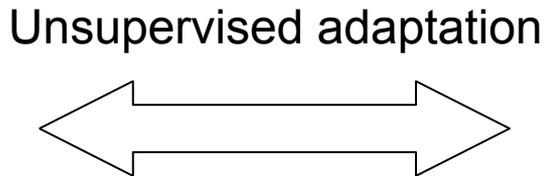
BDD100K
(100K driving videos)



P(Hard) -> Generator -> P(Easy)

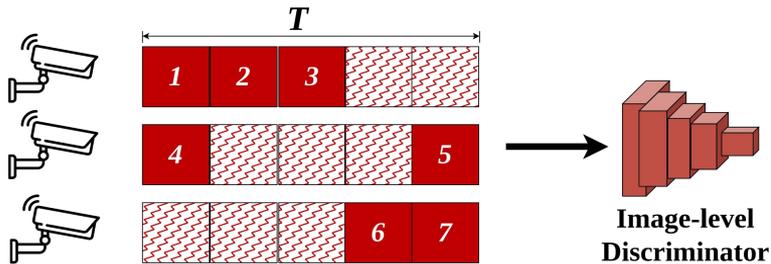


Unlabeled target videos



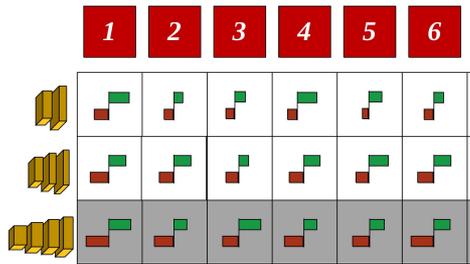
x -> Discriminator -> Easy/Hard

Resource-aware scheduling



All frames are required to be processed within T .

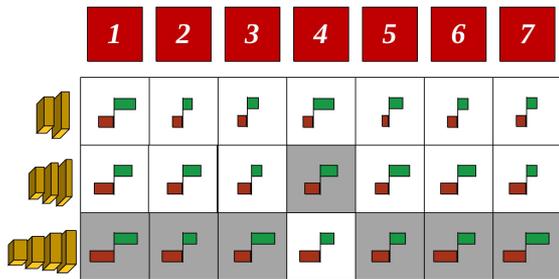
Enhancement Scheduling



Repeat the last step until the total latency $< T$

to the deepest enhancer.

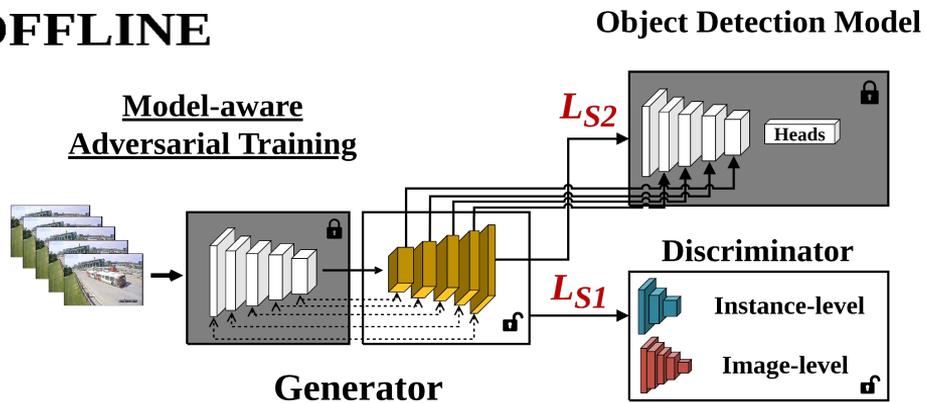
Enhancement Scheduling



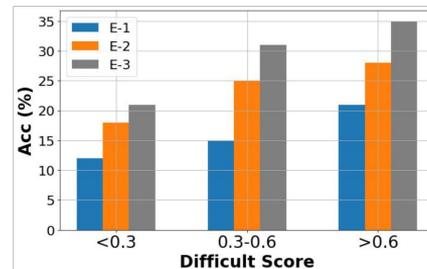
Based on enhancement profiling results, we can select a frame with the minimal marginal accuracy gain and assign it to a weaker enhancer.

Overview

OFFLINE

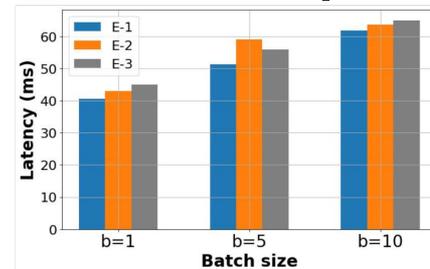


Enhancement Profiling



$$\text{Accuracy} = f(M, D)$$

f_0



$$\text{Cost} = g(M, E)$$

g_0

M: Multi-exit GAN model
D: Image difficulty
E: Execution plan

ONLINE

Performance Estimation

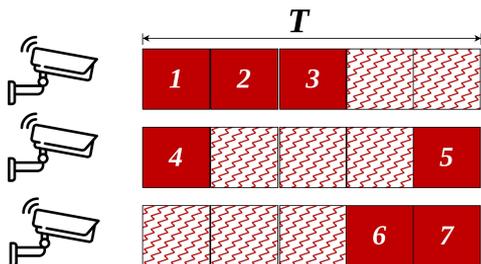
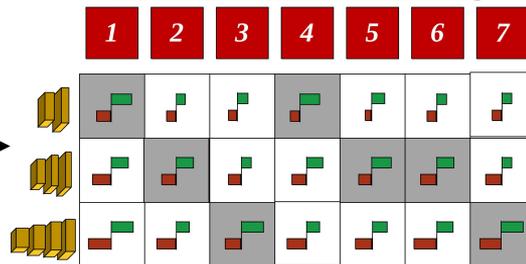


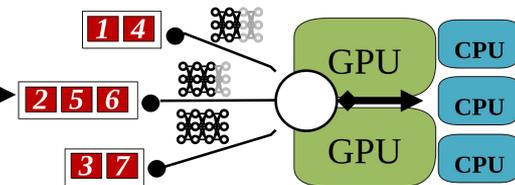
Image-level Discriminator

Enhancement Scheduling



M, E

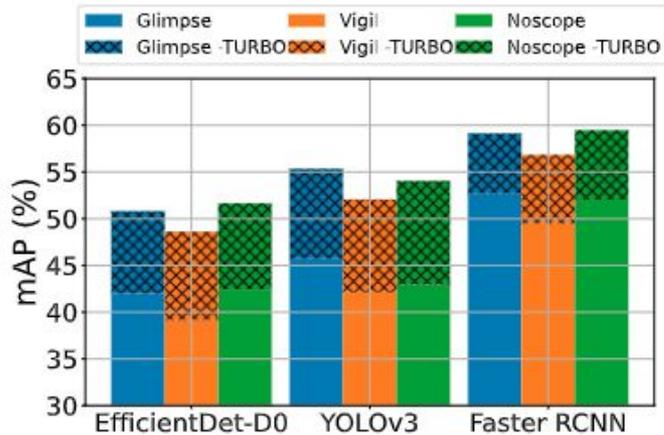
Inference Execution



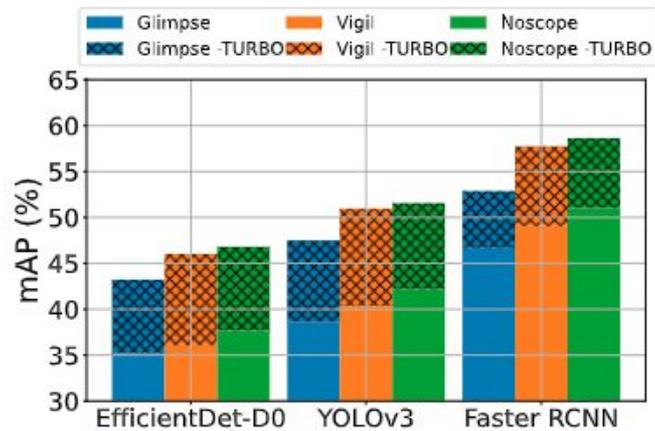
Experiments

- Detectors: YOLOv3, Faster RCNN, EfficientDet-D0.
- Test platforms: Nvidia Tesla V100 and Tesla T4.
- Testing Dataset: UA-DETRAC and AICity.
- Video analytics pipeline:
 - Glimpse: temporal pruning
 - Vigil: model pruning
 - NoScope: temporal pruning + model pruning

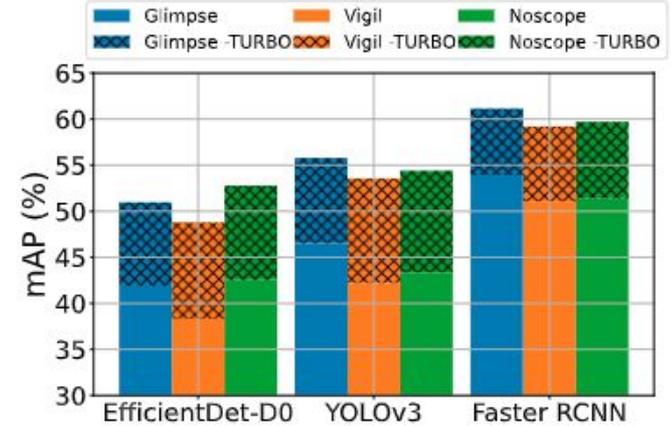
End-to-end results (Accuracy)



UA-DETRAC & T4



AICity & T4

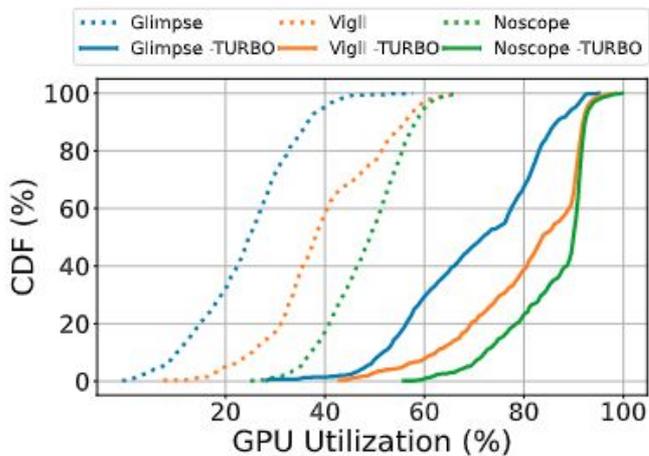


UA-DETRAC & V100

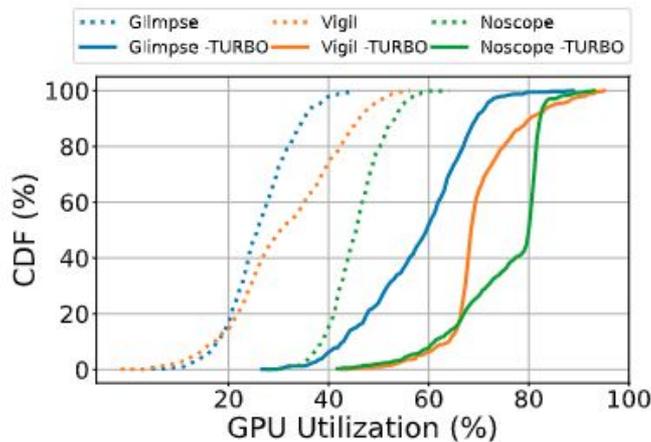
On UA-DETRAC, Turbo achieves 9.35%, 11.34%, 7.27% mAP improvement on average for 3 models.

Usually, we can achieve the maximum mAP improvements on Vigil. It is because model pruning groups most hard frames for Turbo.

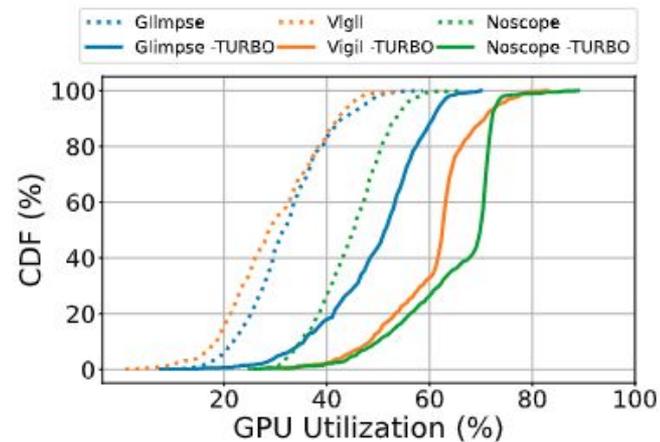
End-to-end results (Idle GPU)



(a) EfficientDet-D0



(b) YOLOv3



(c) Faster RCNN

UA-DETRAC & T4

Summary

- Even on advanced video analytics pipelines, idle computing resources are common but ignored.
- Turbo **selectively** enhances incoming frames based GPU resource availability via a **detector-specific GAN** and **resource-aware scheduling** algorithm.
- Turbo achieves 7.27-11.34% mAP improvements by judiciously allocating 15.81-37.67% GPU idle resources.

