#### **TOSHIBA**

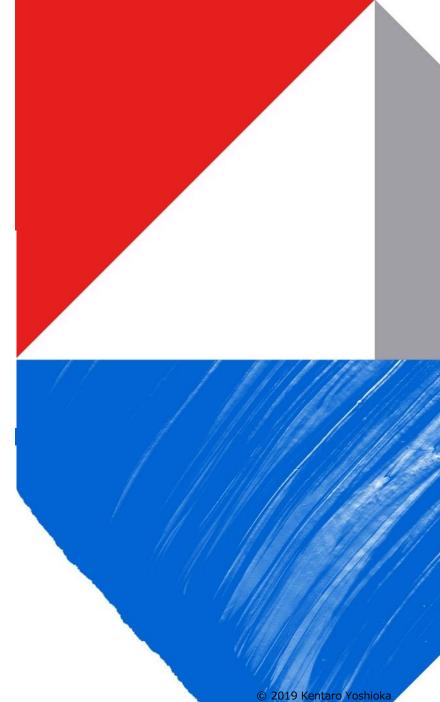


## Dataset Culling: Towards Efficient Training of Distillationbased Domain Specific Models

K.Yoshioka<sup>(1)(2),</sup> E. Lee<sup>(2)</sup>, S. Wong<sup>(2)</sup>, M. Horowitz<sup>(2)</sup> (1) Toshiba

(2) Stanford University

IEEE ICIP 2019 Sept. 25



### Introduction

Deep Learning based object detection has excellent accuracy.
e.g. Vision for security, infrastructure, transportation..

#### Cost?

- Requires many GPU-hours, difficult to scale.
- Has accuracy-cost tradeoff.

101-layer Resnet: Imagenet accuracy <u>78%</u> 10-layer Resnet: Imagenet accuracy <u>60%</u>

### How can we break this tradeoff?

### **Introduction: Domain Specific Models**

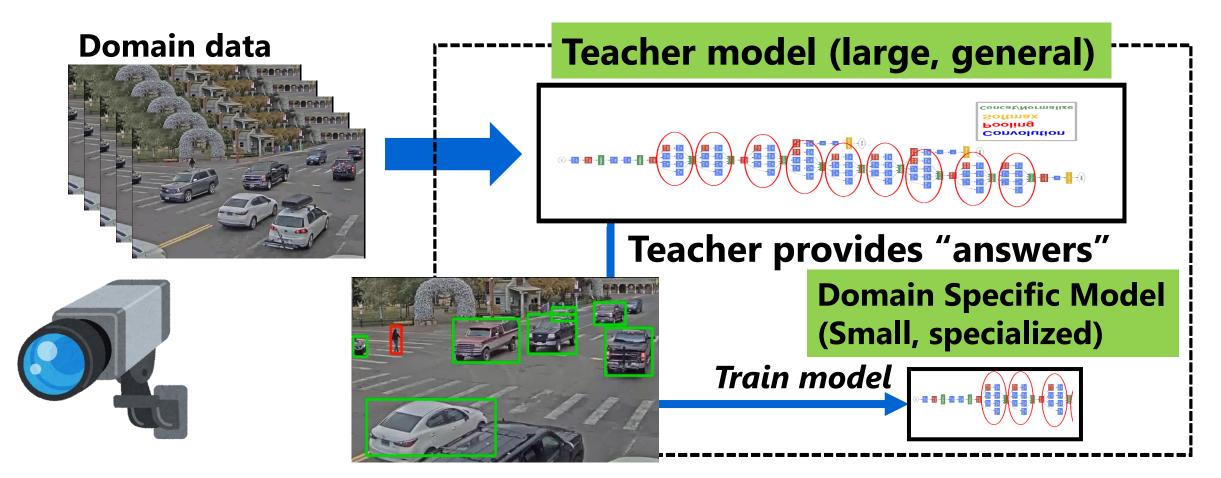
- Training compact domain specific models (DSMs) [1,2]
  - DSMs: a specialized model for specific env. {conference room, your house, your office, etc.}
- Cuts down computation cost <u>5-20x</u>



[1]D. Kang, "Noscope: optimizing neural network queries over video at scale," [2]R.Mullapudi "Online model distillation for efficient video inference,"

### **Introduction: What is Distillation?**

- Teacher model teaches the small student model to learn
  - Works without human interference



### **Introduction: The Problem**

- Can gather lots of training data easily..
  - A day's worth of surveillance data
  - =<u>86,400 images</u> @ 1FPS



- Training 86,400 images require <u>over 100 GPU-hours</u> (Nvidia K80 on AWS) to train.
  - Unable to scale to deploying thousands of cameras

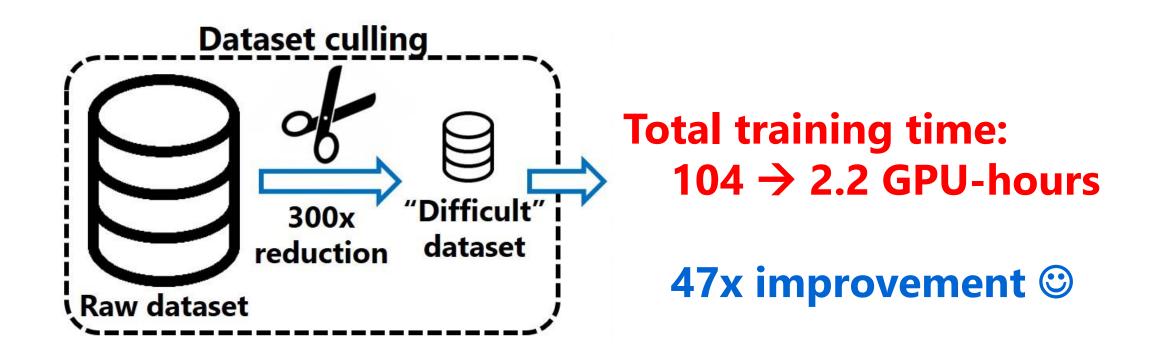
Reducing the DSM training cost has not been explored.

# **Dataset Culling**



### **Basic Idea of Dataset Culling**

- Reduces the dataset size <u>300x</u>
  - Culls only <u>"Easy"</u> data; model accuracy is not harmed



#### What is good training data?

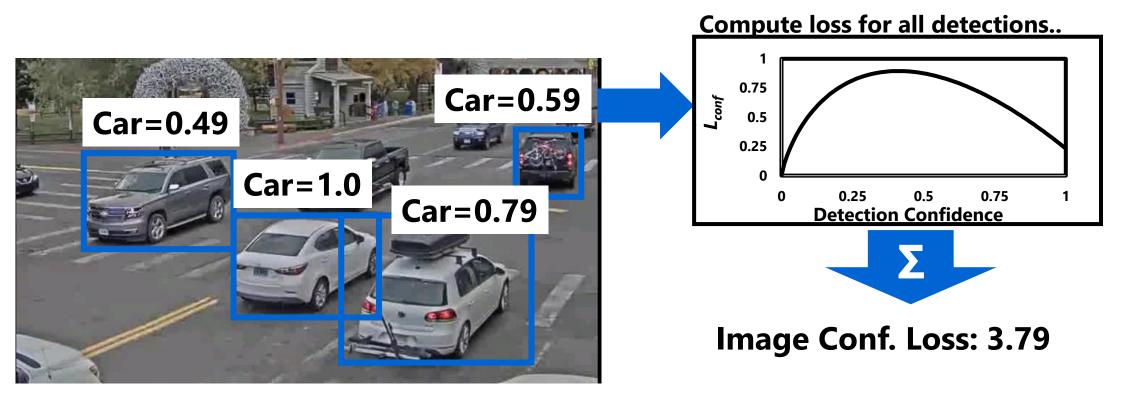
• <u>"Difficult" data</u> which the model makes a lot of mistakes.

- No backprop is done if the model can perfectly predict.
  - $\rightarrow$  Does not contribute to training.
- Comparing teacher-student predictions are costly...

### Can we assess from student predictions only?

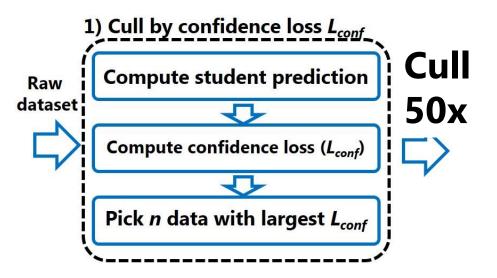
#### How can we pick good training data?

- Quantify good data by proposed "confidence loss"
  - Assesses the difficulty of prediction from the output probability



### **Dataset culling pipeline**

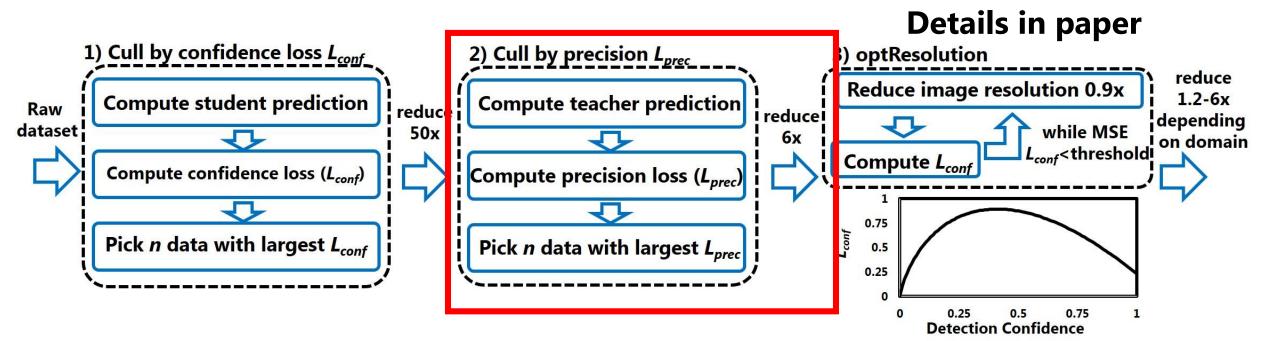
- First, cull dataset using <u>only the student model</u>
  - Culls out majority of the data first (50x).
  - Cheap; does not require costly teacher inference.



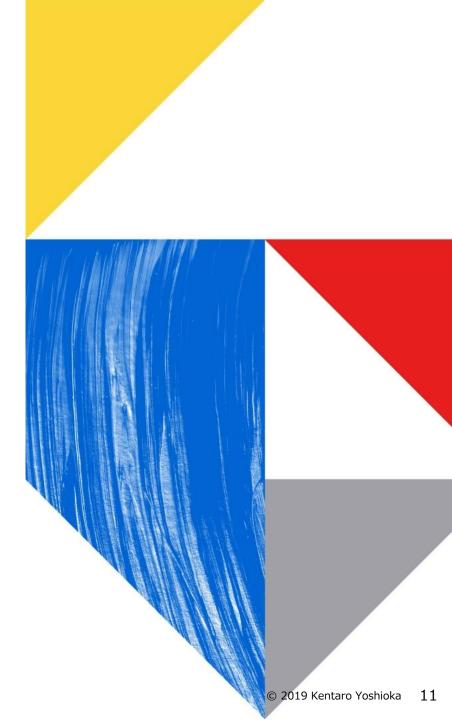
### **Dataset culling pipeline**

#### Then, conduct a secondary culling using both teacher-student predictions.

- Directly determine errors the student makes.
- Data is culled up to <u>300x</u> by the pipeline.



## Experiments

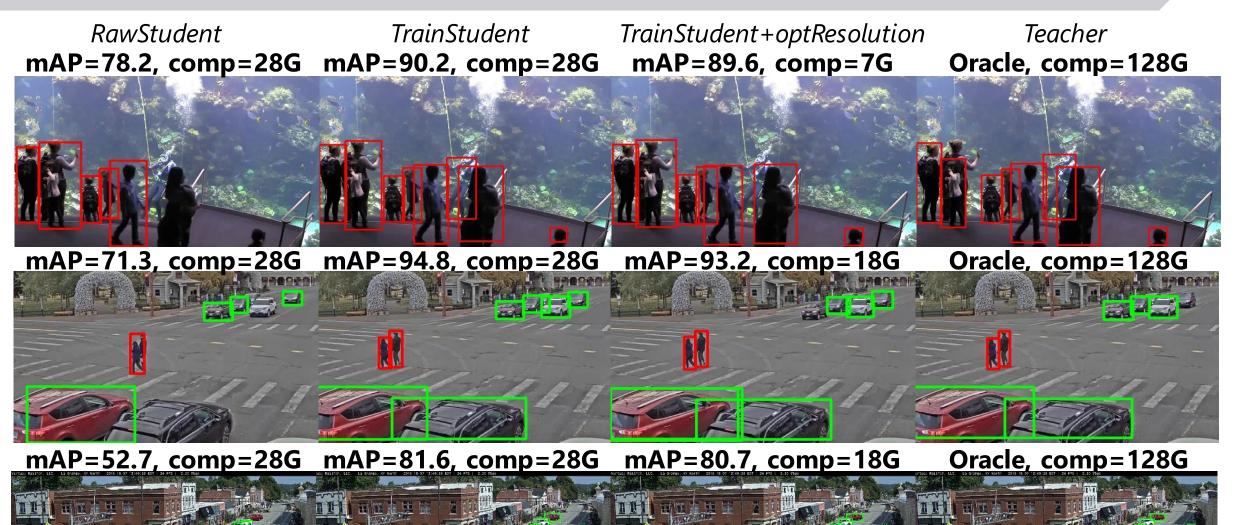


### **Experiment setups**

- Models pretrained on MS-COCO:
  - Student: Resnet-18 based Faster-RCNN
  - Teacher: Resnet-101 based Faster-RCNN
- Dataset: 8 custom videos acquired from Youtube.
  - Train: first 24-hours
  - Validation: Subsequent 6-hours
  - Utilize teacher output as ground-truths

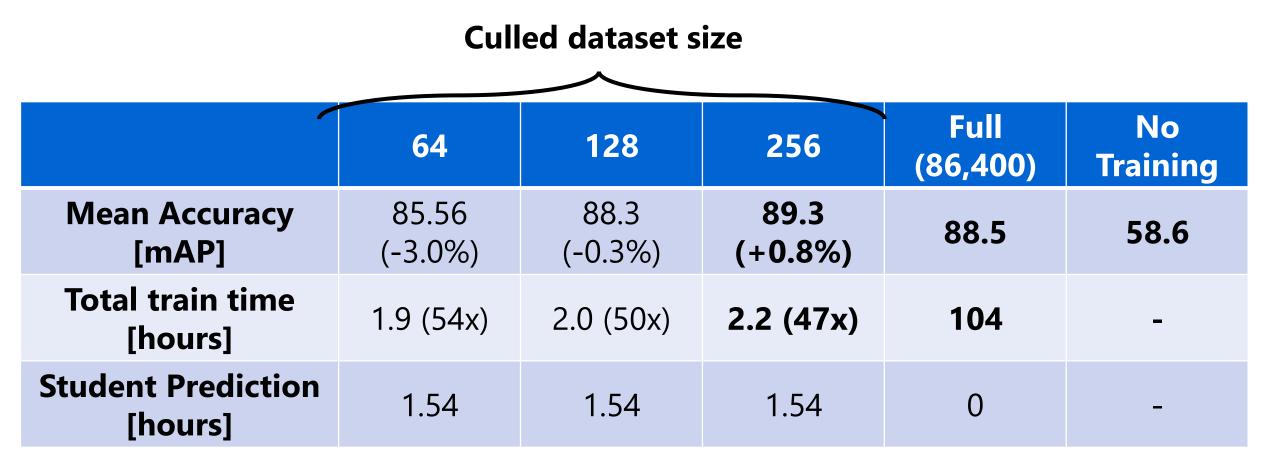


### **Qualitative results**



### **Quantitative Results**

• Can cull the dataset size to <u>300x</u>, without accuracy drops or even with improvements.



### Conclusions

• While DSMs can reduce the inference cost, training them can take many GPU-hours.

• We proposed Dataset Culling, which reduces the DSM training cost by 47x.

- •Only easy to predict data are culled to minimize the accuracy drop.
- Evaluated on our long-duration dataset, we saw little to no accuracy penalty even with culling.

**Codes and dataset available:** 

https://github.com/kentaroy47/DatasetCulling

### **Ablation study**

- Entropy implements the loss function for active learning.
- Using teacher-student comparisons achieve best accuracy (Precision)
- Our dataset culling pipeline with Confidence + Precision has the best tradeoff of accuracy and training time.

		0		-		
Filtering strategy	Intermittent Samp.	Entropy[9]	Confidence	Precision	Confidence + Precision	Full dataset
mAP	0.731	0.866	0.911	0.954	0.948	0.958
GPU hours	0.15	1.7	1.7	8.0	2.0	104