



# MathWorks #2

## Classifying Object Behavior to Enhance the Safety of Autonomous Vehicles

### AI Studio Final Presentation

Break Through Tech AI Boston @ MIT  
January 23, 2024



# Introductions



# Meet Our Team!



**Pamela Melgar**  
Tufts University



**Elena Wang**  
Smith College



**Kashish Gupta**  
Worcester Polytechnic Institute



**Rachel Ma**  
Northeastern University



**Vanessa Bellotti**  
Tufts University



**Nyah Lalimarmo**  
Simmons University



# Our AI Studio TA and Challenge Advisor



**Maria Elena Gavilan Alfonso**  
Challenge Advisor



**Keith Murray**  
AI Studio TA



# Presentation Agenda

1. Project Overview
2. Data Understanding and Data Preparation
3. Transfer Learning & Foundational Model
4. Model Training and Evaluation
5. Final Thoughts
6. Questions



# AI Studio Project Overview



“

Fine-tuning the detection of pedestrians  
and cyclists near autonomous vehicles  
using Deep Learning (Transfer Learning)





# Business Impact

- Increasing '**public trust**' in self-driving cars
  - Insight into *potential* dangers
  - Potentially smoother driving, better identification
- Accurate object detection = **safe critical decisions**
- Transfer Learning is '**cost-effective**'
  - Cut costs of building model from scratch





# Our goals

---

1. Use **real sensor data** collected at Boston to aid the development of autonomous vehicles
2. Explore the efficacy of leveraging **transfer learning** within an autonomous vehicle object classification problem (for pedestrians and cyclists)
  - a. Fine-tune an object detection model that demonstrates high accuracy in identifying pedestrians and cyclists
3. Add-in a 3D element to the object detection model by implementing LIDAR data (To explore in the future)



# Our Approach

## Data preparation

Explored nulmages data and created training and test sets

## Training

Transfer Learning



## Training Preparation

Downloaded TensorFlow pretrained models and explored the Object Detection API

## Evaluation

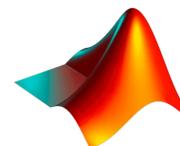
Used metrics like precision and recall to fine-tune the model



# Resources We Leveraged



TensorFlow



MATLAB®



NUSCENES

## Training

TensorFlow

TensorFlow Core

Overview

Tutorials



Deep Learning  
Onramp  
(MATLAB)

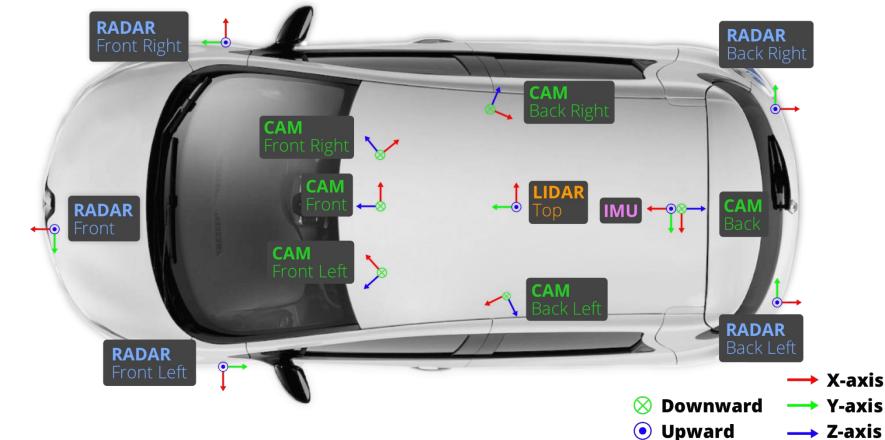
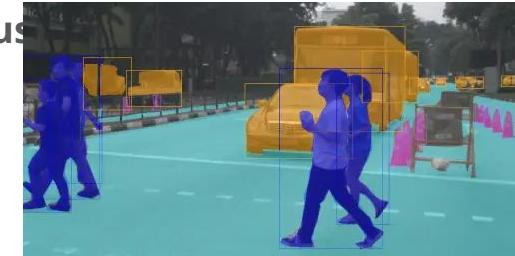


# Data Understanding & Data Preparation



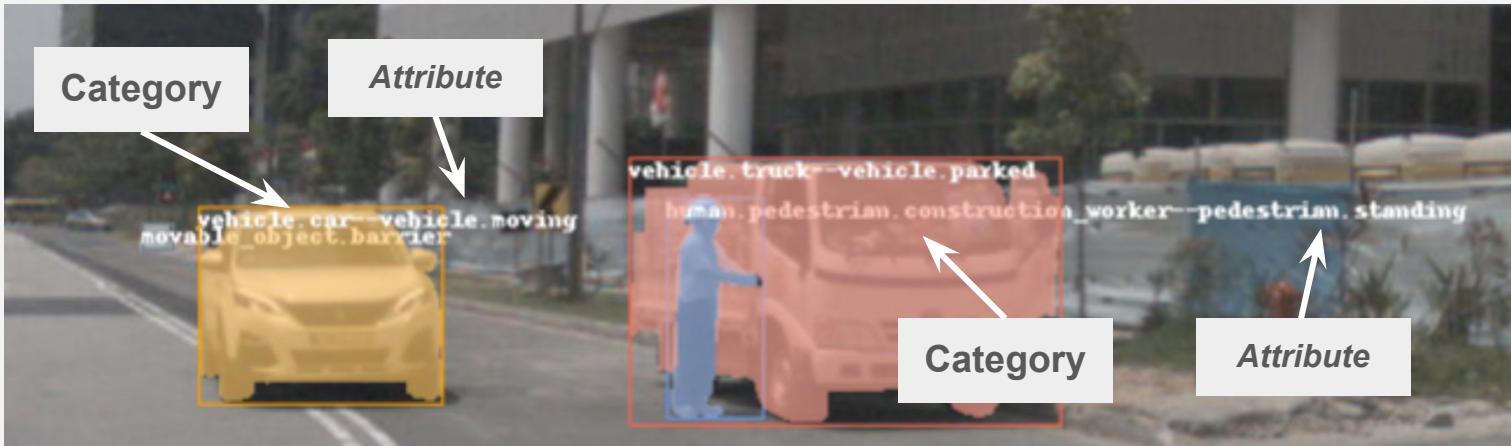
# Dataset Overview - nulmages

- ***nulmages*** is a subset of ***nuScenes***, a public large-scale **autonomous driving dataset** developed by [Motional](#)
- **93k 2D annotated images** mined for diversity
- Full sensor suite (1x LIDAR, 5x RADAR, **6x camera**, IMU, GPS)
- **800k annotated foreground objects** with 2D bounding boxes and instance masks





# Example of nulmages



```
def store_single_image(sample_record):
    key_cam_token = sample_record['key_camera_token'] #get token in order to gain access to sample_data
    sample_data_record = nuim.get('sample_data', sample_record['key_camera_token'])

    image_filename = "example_image_name"
    nuim.render_image(key_cam_token, annotation_type='objects', with_category=True, with_attributes=True, out_path='/content/sample_data/images/' + image_file
```



# Data Selection

- Data already cleaned
- Features, annotations and attributes
- Only want pedestrians and cyclists

```
for cat in nuim.category:  
    print(cat['name'])  
  
animal  
flat_driveable_surface  
human.pedestrian.adult  
human.pedestrian.child  
human.pedestrian.construction_worker  
human.pedestrian.personal_mobility  
human.pedestrian.police_officer  
human.pedestrian.stroller  
human.pedestrian.wheelchair  
movable_object.barrier  
movable_object.debris  
movable_object.pushable_pullable  
movable_object.trafficcone  
static_object.bicycle_rack  
vehicle.bicycle  
venicie.bus.bendy  
vehicle.bus.rigid  
vehicle.car  
vehicle.construction  
vehicle.ego  
vehicle.emergency.ambulance  
vehicle.emergency.police  
vehicle.motorcycle  
vehicle.trailer  
vehicle.truck
```

```
for att in nuim.attribute:  
    print(att['name'])  
  
cycle.with_rider  
cycle.without_rider  
pedestrian.moving  
pedestrian.sitting_lying_down  
pedestrian.standing  
vehicle.moving  
vehicle.parked  
vehicle.stopped  
vehicle_light.emergency.flashing  
vehicle_light.emergency.not_flashing  
vertical_position.off_ground  
vertical_position.on_ground
```

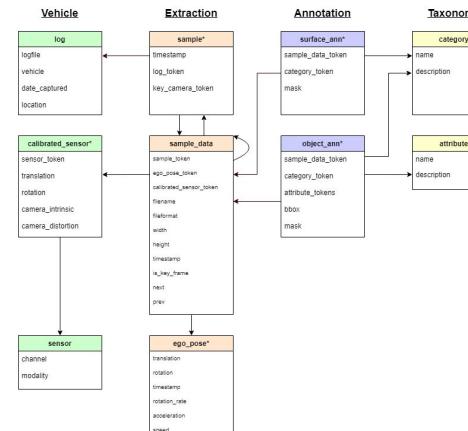


# Converting into XML format



nuimages schema

Asterisks (\*) indicate modifications compared to the nuScenes schema.



```
<annotation>
  <folder>vehicles</folder>
  <filename>ff9435ee-ba7e-4d32-93b
  <path>E:\vehicles\ff9435ee-ba7e-
  <size>
    <width>800</width>
    <height>598</height>
    <depth>3</depth>
  </size>
  <segmented>0</segmented>
  <object>
    <name>truck</name>
    <bndbox>
      <xmin>7</xmin>
      <ymin>119</ymin>
      <xmax>630</xmax>
      <ymax>468</ymax>
    </bndbox>
  </object>
  <object>
    <name>person</name>
    <bndbox>
      <xmin>40</xmin>
      <ymin>90</ymin>
      <xmax>100</xmax>
      <ymax>350</ymax>
    </bndbox>
  </object>
</annotation>
```

Pascal VOC XML



# Transfer Learning & Foundation Model



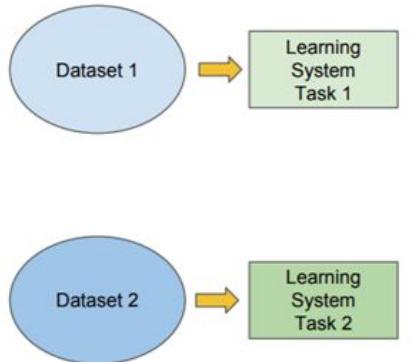
# Why Transfer Learning?

## Traditional ML

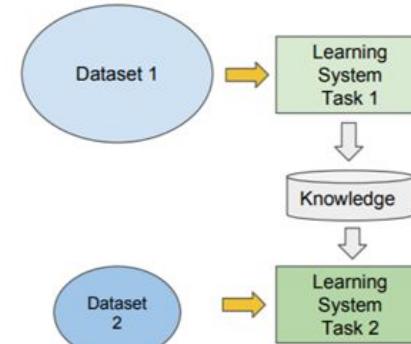
vs

## Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



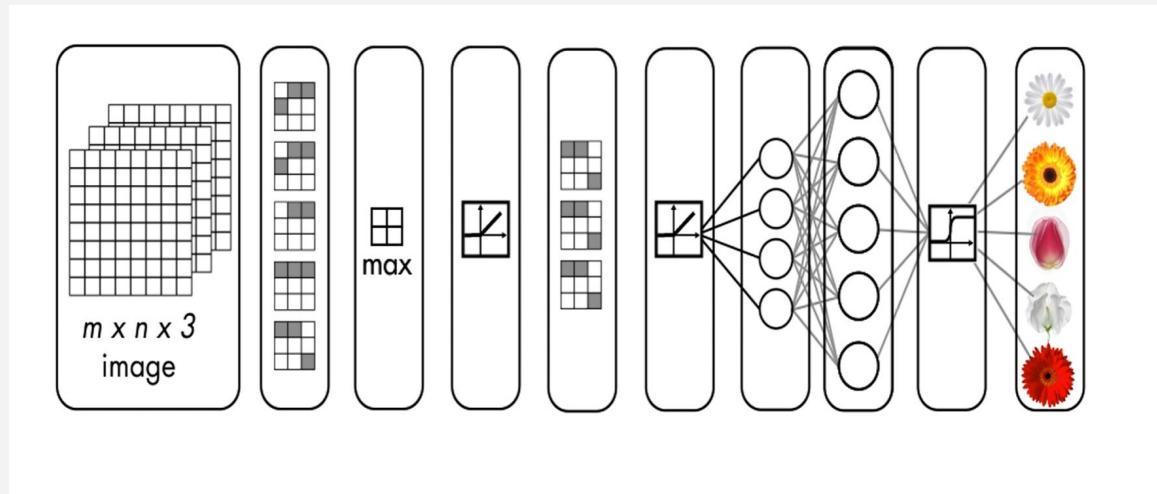
- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data





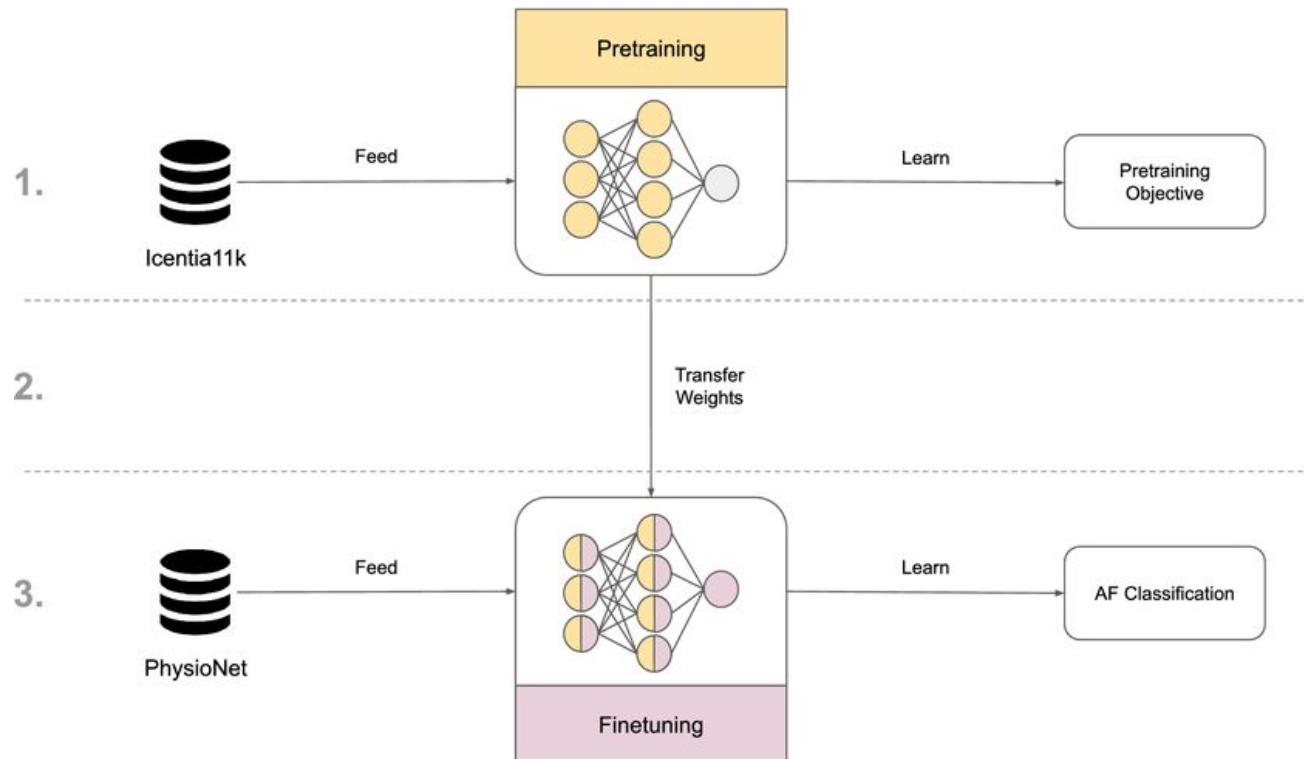
# Visual Representation of Transfer Learning

- Take a pre-trained Network
- Modify and re-train it on **new** data





# Overview of Transfer Learning





# Deep Learning Onramp was useful to get acquainted with Transfer Learning

Self-Paced Online Courses

Home | My Courses

## Deep Learning Onramp

[Start course](#) [Share Course](#) | [Share Certificate & Progress](#)

▼ Perform Transfer Learning

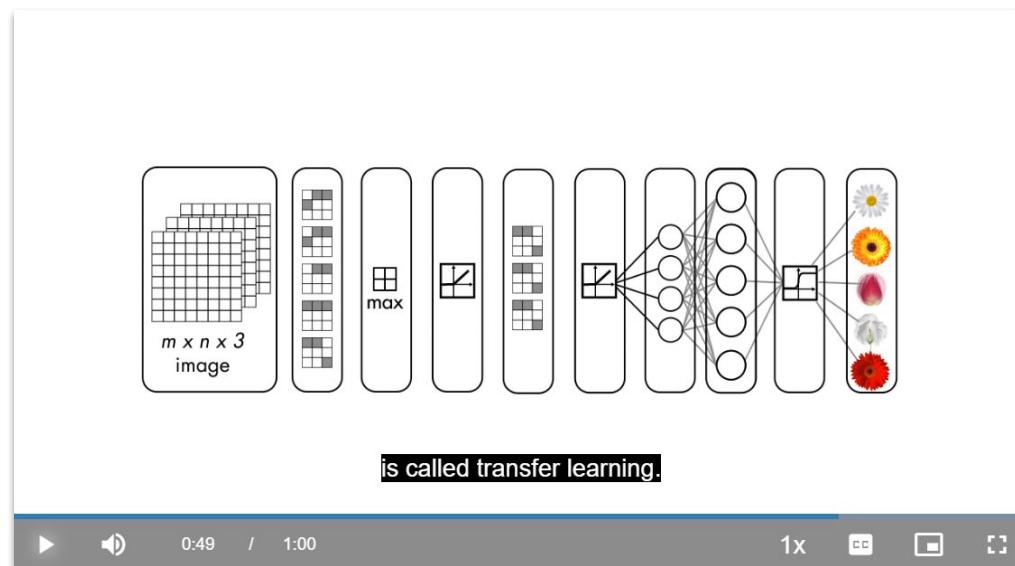
Length: About 1 hour

Modify a pretrained network to classify images.

[Start module](#) [Share Module](#)

Lessons:

- What is Transfer Learning?
- Components Needed for Transfer Learning
- Prepare Training Data
- Modify Network Layers
- Set Training Options
- Train the Network
- Evaluate Performance
- Transfer Learning Summary





# Model Hubs enable access to several pretrained models

Models available in MATLAB:

Network	Size (MB)	Classes	Accuracy %	Location
<a href="#">googlenet</a>	27	1000	66.25	<a href="#">Doc</a> <a href="#">GitHub</a>
<a href="#">squeezenet</a>	5.2	1000	55.16	<a href="#">Doc</a>
<a href="#">alexnet</a>	227	1000	54.10	<a href="#">Doc</a>
<a href="#">resnet18</a>	44	1000	69.49	<a href="#">Doc</a> <a href="#">GitHub</a>
<a href="#">resnet50</a>	96	1000	74.46	<a href="#">Doc</a> <a href="#">GitHub</a>
<a href="#">resnet101</a>	167	1000	75.96	<a href="#">Doc</a> <a href="#">GitHub</a>

## Pretrained EfficientDet Network For Object Detection

This repository provides a pretrained EfficientDet-D0[1] object detection network for MATLAB®.

[Open in MATLAB Online](#)

### Requirements

- MATLAB® R2021a or later
- Deep Learning Toolbox™
- Computer Vision Toolbox™
- Deep Learning Toolbox Converter for ONNX Model Format™ Support Package

MATLAB Deep Learning Model Hub

## TensorFlow 2 Detection Model Zoo

TensorFlow 2.2 Python 3.6

We provide a collection of detection models pre-trained on the [COCO 2017 dataset](#). These models can be useful for out-of-the-box inference if you are interested in categories already in those datasets. You can try it in our inference [colab](#).

They are also useful for initializing your models when training on novel datasets. You can try this out on our few-shot training [colab](#).

Please look at [this guide](#) for mobile inference.

Finally, if you would like to train these models from scratch, you can find the model configs in this [directory](#) (also in the linked `car.gz`).

Model name	Speed (ms)	COCO mAP	Outputs
<a href="#">CenterNet HourGlass104 512x512</a>	70	41.9	Boxes
<a href="#">CenterNet HourGlass104 Keypoints 512x512</a>	76	40.0/61.4	Boxes/Keypoints
<a href="#">CenterNet HourGlass104 1024x1024</a>	197	44.5	Boxes
<a href="#">CenterNet HourGlass104 Keypoints 1024x1024</a>	211	42.8/64.5	Boxes/Keypoints
<a href="#">CenterNet Resnet50 V1 FPN 512x512</a>	27	31.2	Boxes
<a href="#">CenterNet Resnet50 V1 FPN Keypoints 512x512</a>	30	29.3/50.7	Boxes/Keypoints
<a href="#">CenterNet Resnet101 V1 FPN 512x512</a>	34	34.2	Boxes
<a href="#">CenterNet Resnet50 V2 512x512</a>	27	29.5	Boxes

TensorFlow 2 Model Zoo

# Model Architecture Selection

Selected several object detection models from the [\*\*TensorFlow 2 Detection Model Zoo\*\*](#)

Picked **4 architectures** to test from each group:

Faster R-CNN ResNet101 V1 1024x1024

CenterNet Resnet101 V1 FPN 512x512

SSD ResNet101 V1 FPN 640x640 (RetinaNet101)

EfficientDet D1 640x640

Based on **3 factors**:

Speed

COCO mAP (mean Average Precision on COCO dataset)

Outputs (keypoints, bounding boxes, masks, or multiple)

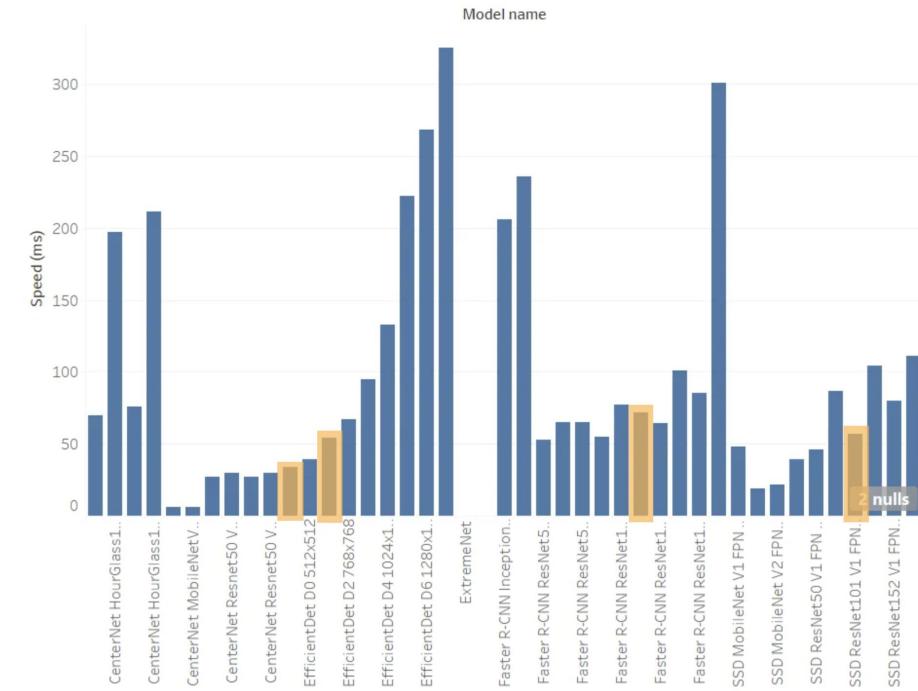
After model testing on a neutral dataset, we observed that **Faster R-CNN** is best for our purposes



# Model Comparison

Model Name	Speed (ms)	mAP [precision]	Outputs
<b>Faster R-CNN</b> <b>ResNet101 V1</b> <b>1024x1024</b>	<b>72</b>	<b>37.1</b>	<b>Boxes</b>
CenterNet Resnet101 V1 FPN 512x512	34	34.2	Boxes
EfficientDet D1 640x640	54	38.4	Boxes
SSD ResNet101 V1 FPN 640x640 (RetinaNet101)	57	35.6	Boxes

Comparison of speed across all of the architectures



# Comparison on beach sample



Faster R-CNN ResNet101  
V1 1024x1024



## CenterNet Resnet101 V1 FPN 512x512

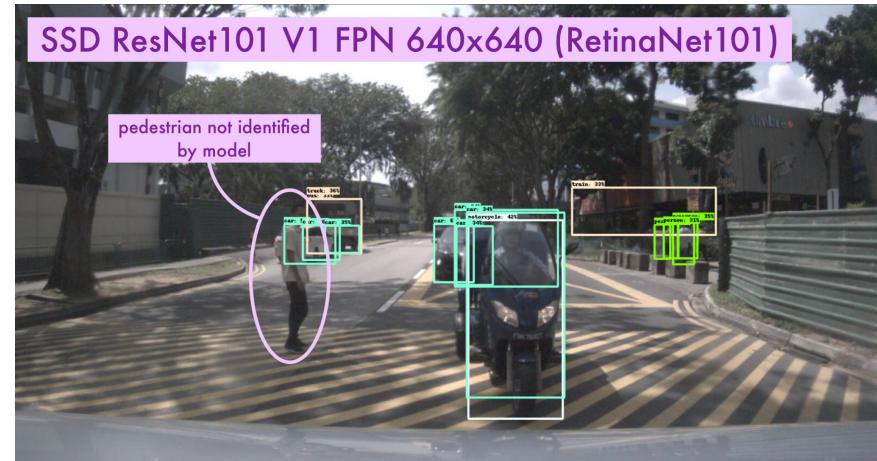
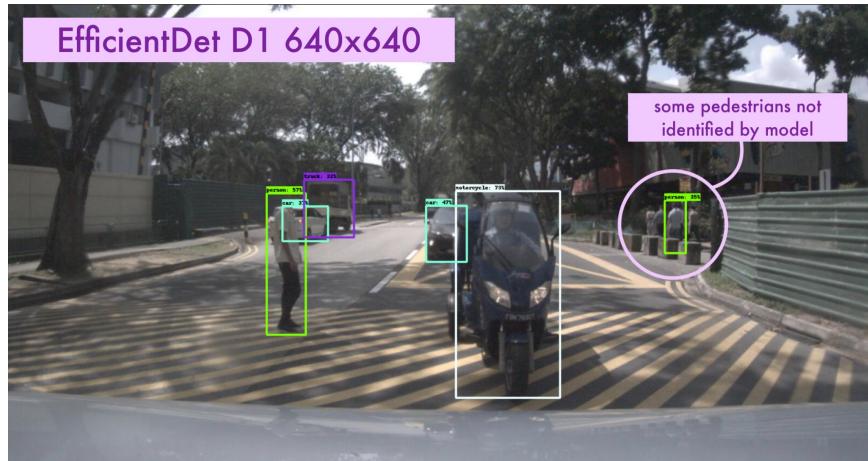
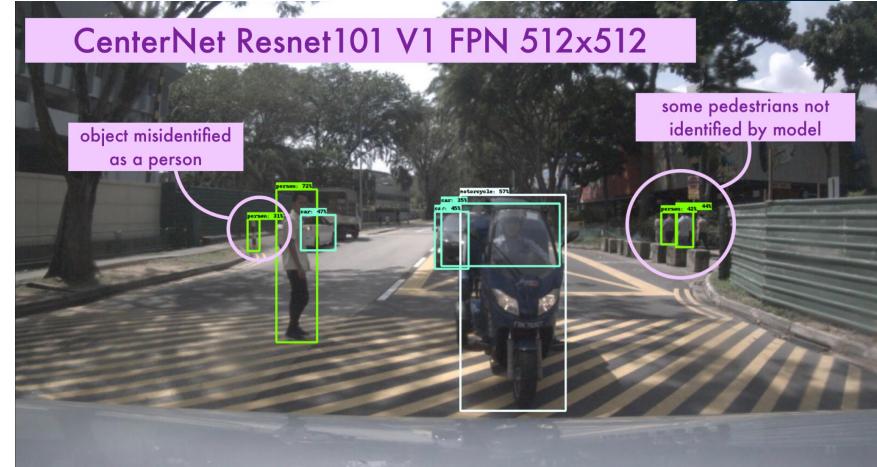
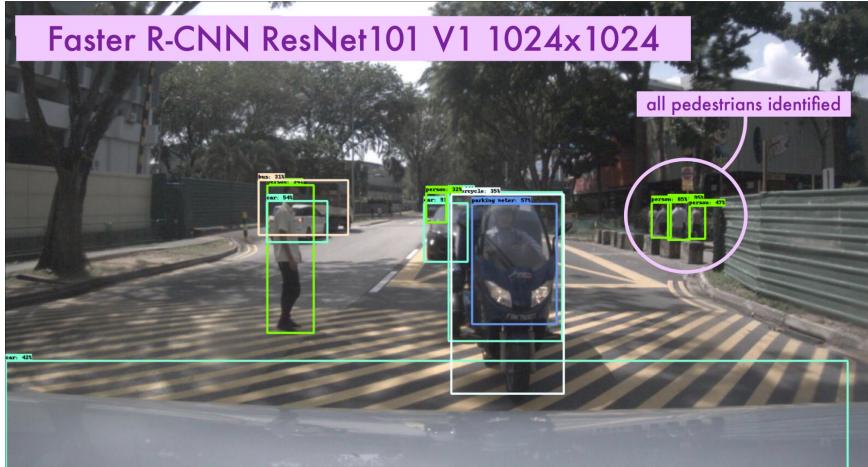


EfficientDet D1 640x640



SSD ResNet101 V1  
FPN 640x640 (RetinaNet101)

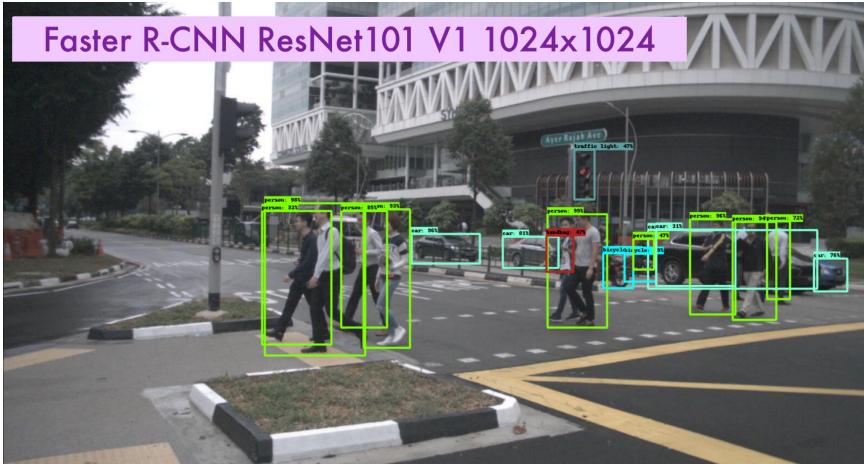
# Comparison on nulimages - part 1



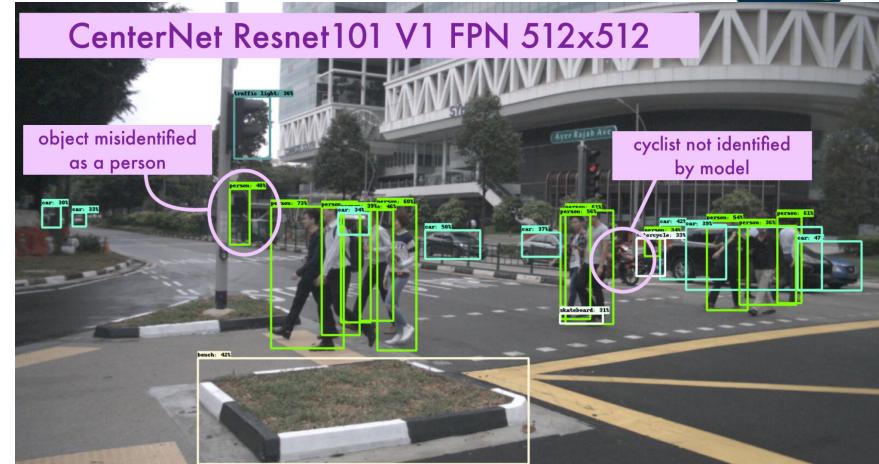
# Comparison on nulimages - part 2



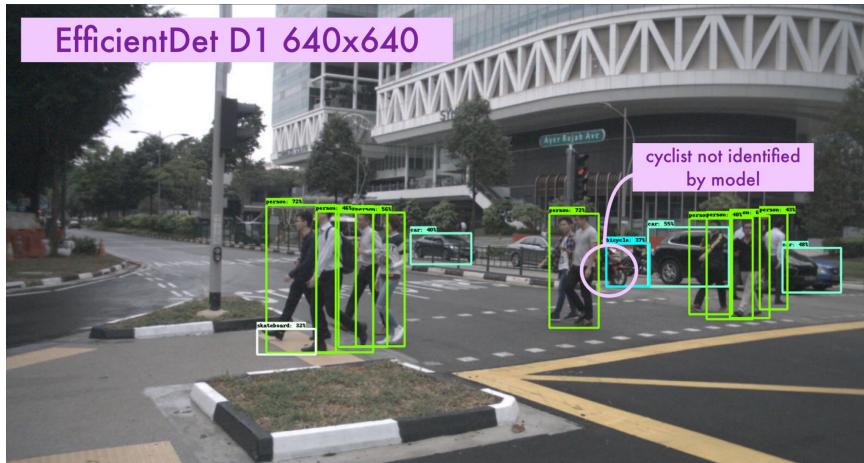
Faster R-CNN ResNet101 V1 1024x1024



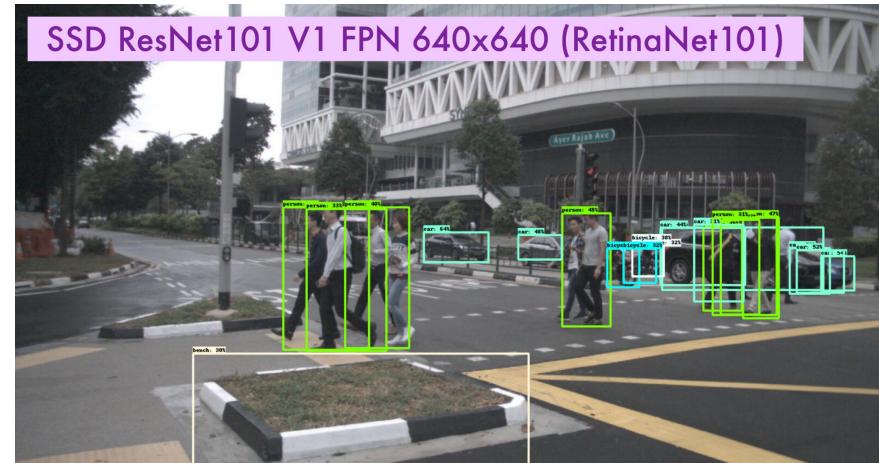
CenterNet Resnet101 V1 FPN 512x512



EfficientDet D1 640x640



SSD ResNet101 V1 FPN 640x640 (RetinaNet101)





# Customizing Pretrained Object Detectors

- Existing pre-trained networks for object detection can identify people, bikes and cars, but they provide little to no information to the specifics of the pedestrians (standing, moving, etc.)
- Dataset used in this project contains all the additional details needed to customize the detection of pedestrians and people riding bicycles or motorcycles.
- Architectures pre-selected can be used in the model training step.



# Model Training & Evaluation



# Environments We Utilized





# Data Decisions for Training

**500  
total  
images**

Limited number of images out of the 87k available

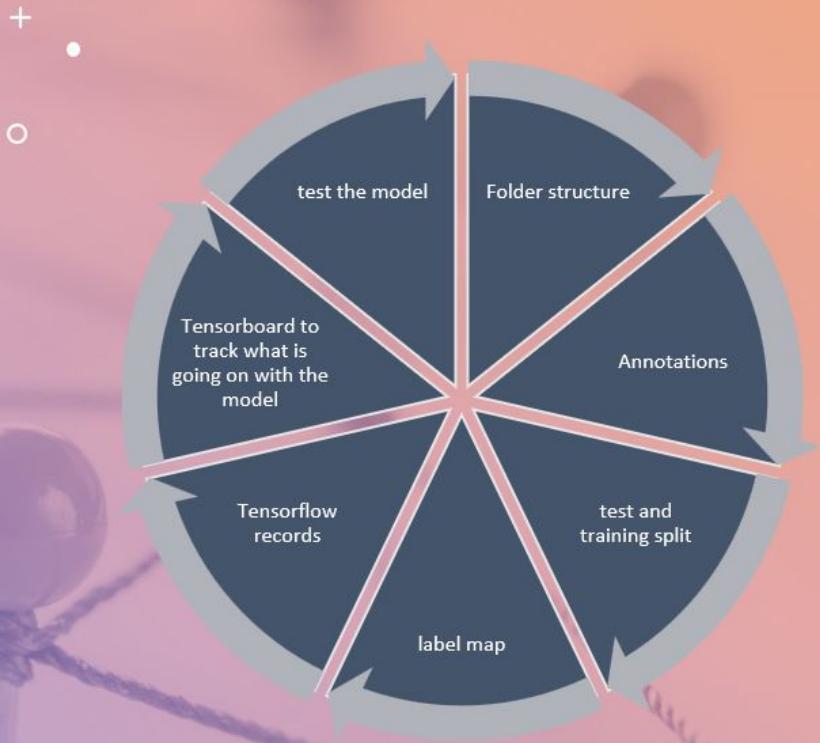
**FRONT  
CAM**

Images used from FRONT Cameras only

**Moving**

Must include at least one moving pedestrian or cycle with rider

# The training process





# The training process - New Classes for Detection

Examples of classes to train on:

'Human.pedestrian.adult-pedestrian.moving'

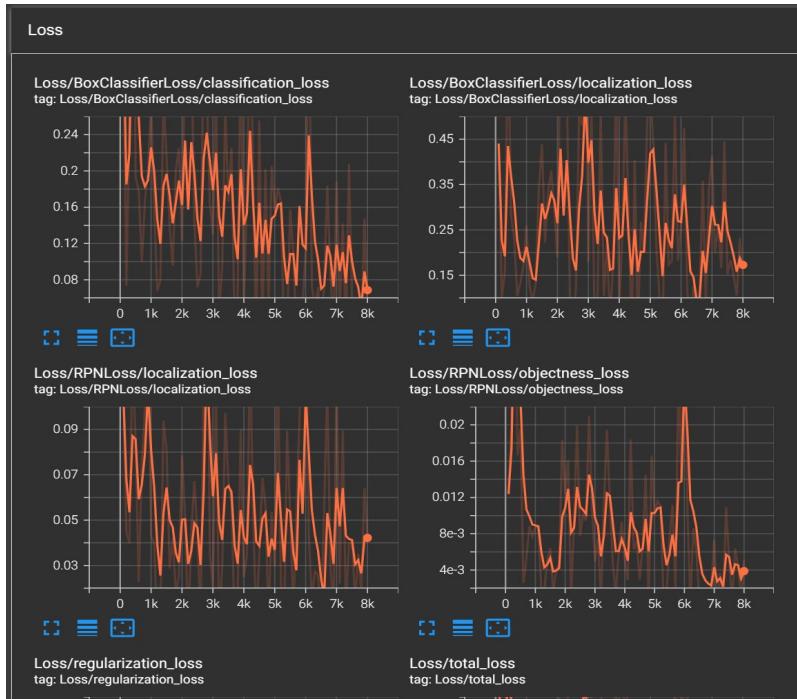
'Human.pedestrian.child-pedestrian.moving'

A combination of category and attribute to make the classes distinctive enough. In total, we trained the object detector to detect 10 different types of humans moving in the image.



# Training Results - Improper Data

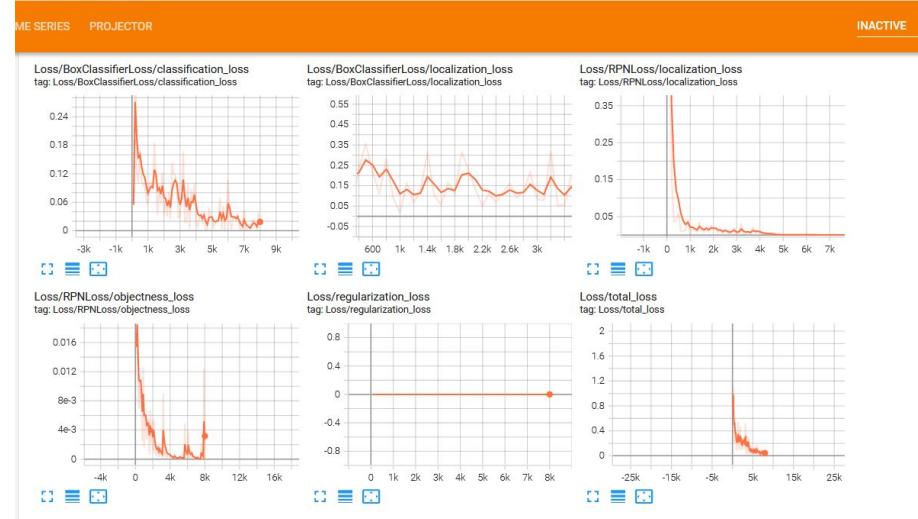
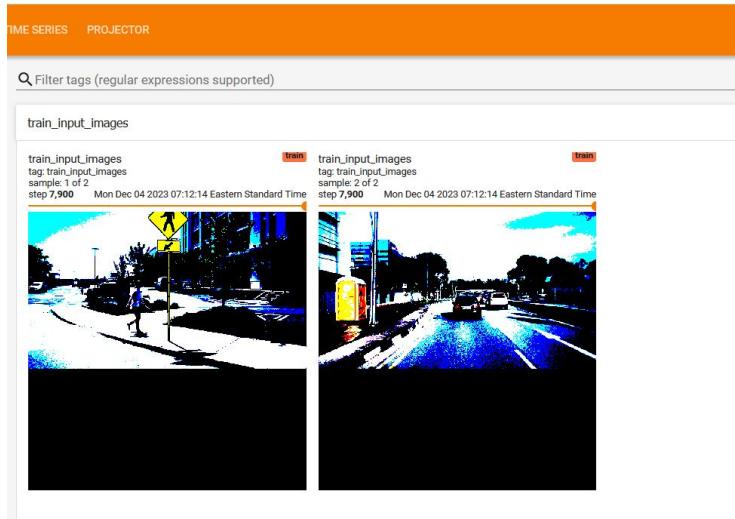
Fast RCNN ResNet 101(1024x1024)





# Training Results - First pretrained model

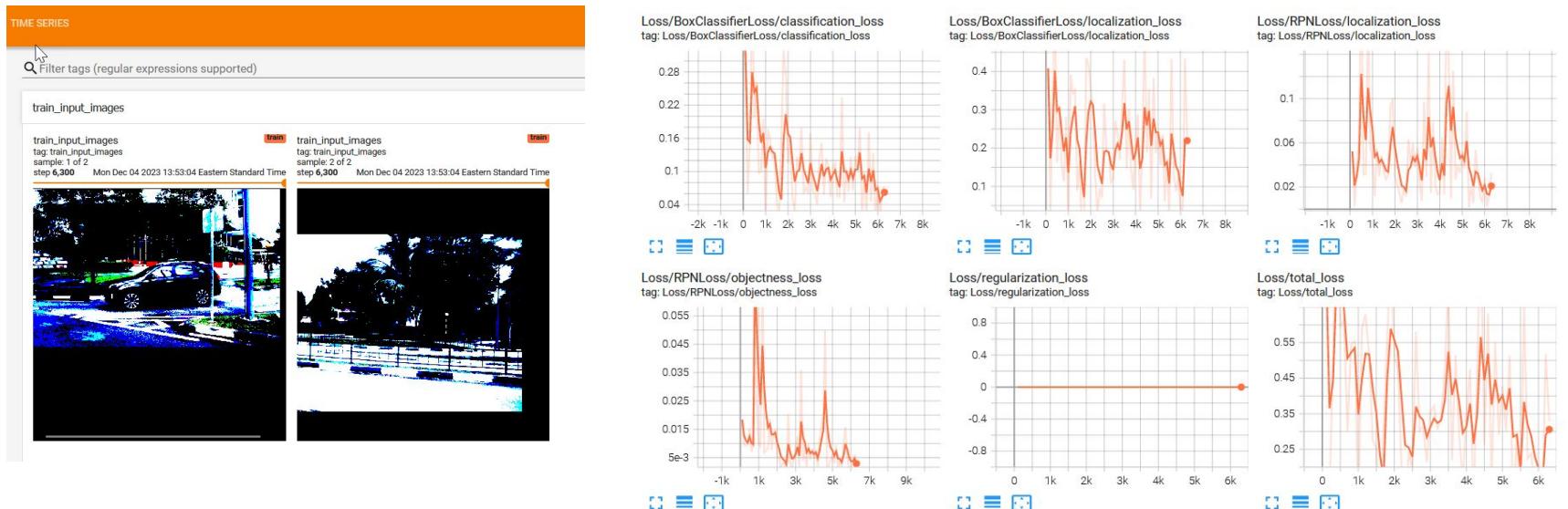
Fast RCNN ResNet 50 (640x640)





# Training Results - Second pretrained model

Fast RCNN ResNet 101(1024x1024)



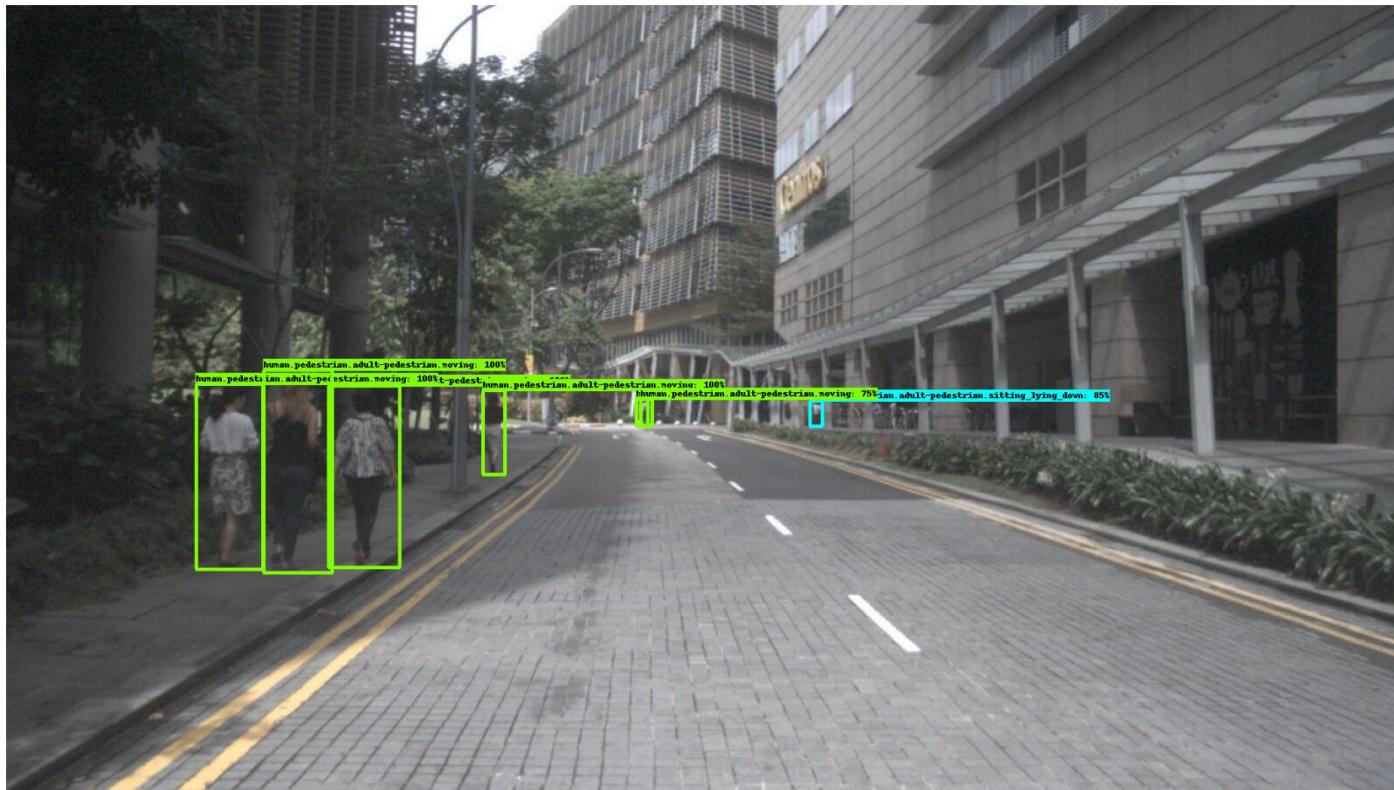


# Testing the Model (before detection)



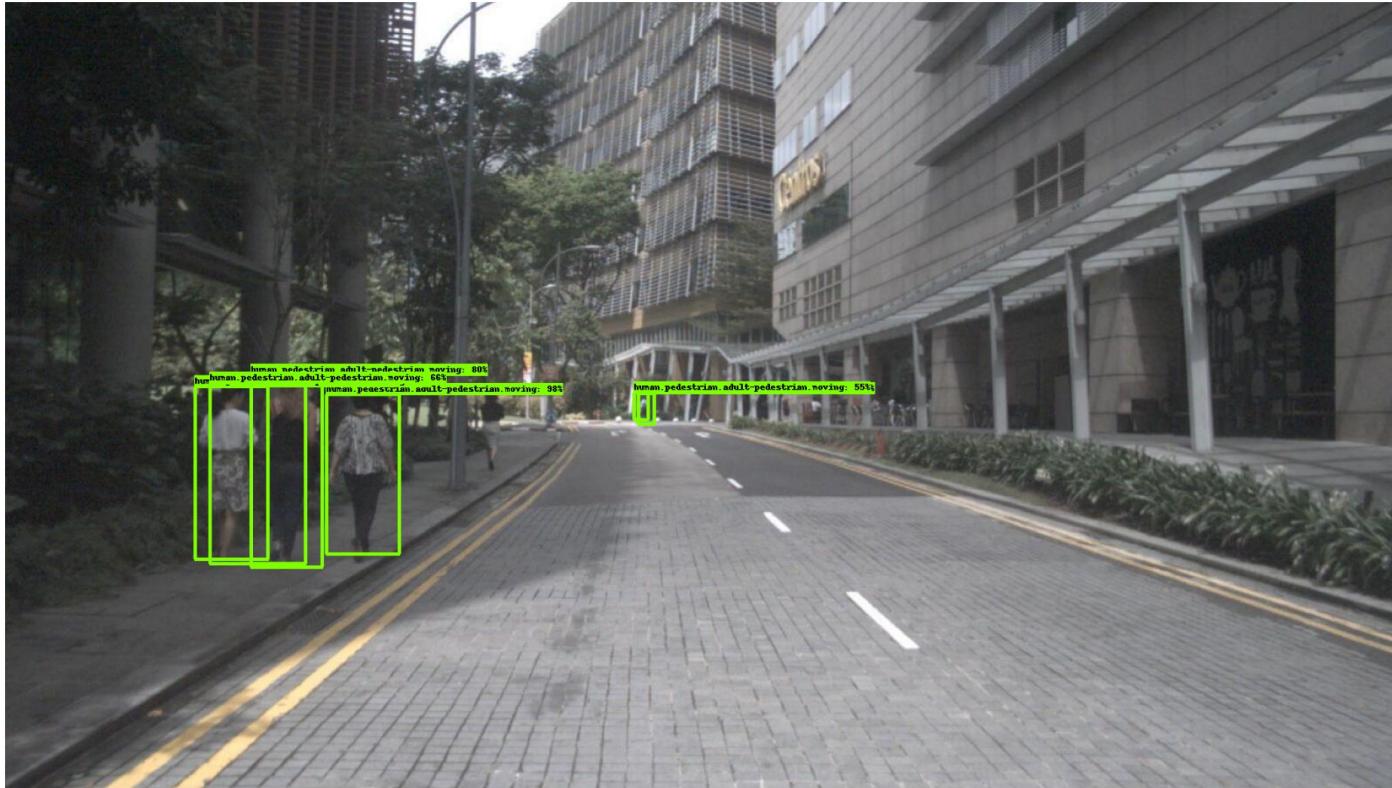


# Testing the Model (with model trained #1)



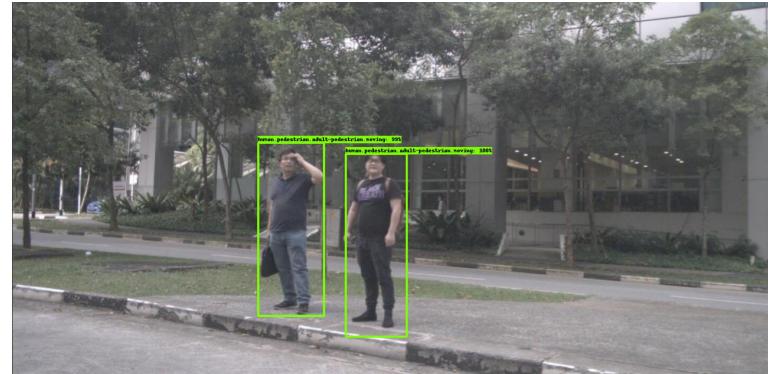
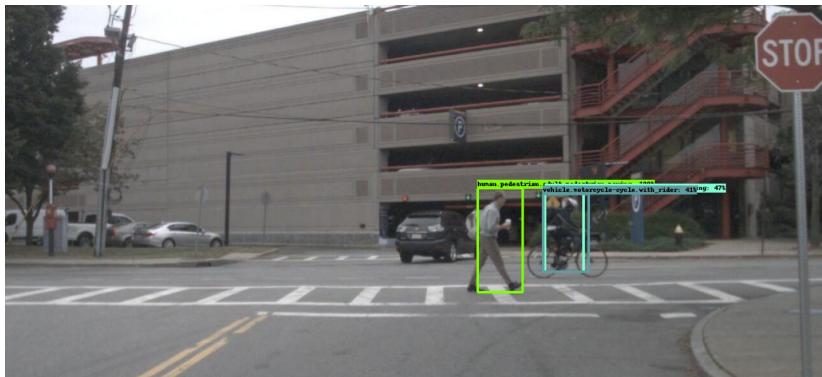


# Testing the Model (with model trained #2)

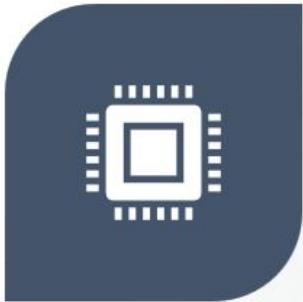




# Testing the Model



# Insights and Key Findings



TRANSFER LEARNING ENABLES THE TRAINING OF  
HIGHLY SPECIALIZED DEEP LEARNING NETWORKS  
THAT DO CUSTOM OBJECT DETECTION



HIGHLY PRECISE MODELS CAN BE TRANSFER LEARNED  
USING A SMALLER DATASET AND LESS COMPUTE  
THAN IF WE HAD TRAINED A BASE DEEP NEURAL  
NETWORK FROM SCRATCH



DATA INFRASTRUCTURE AND THE IMPORTANCE OF  
REPRODUCIBILITY IN PIPELINES



# Further exploration: Using the model in MATLAB

- Using the Deep Learning Toolbox, TensorFlow models can be imported into MATLAB



Puzzle:  
TensorFlow 2  
models with  
“SavedModel”  
format into  
MATLAB - How  
best to import  
models with this  
format?



# Next Step: Access LIDAR Data from nuScenes

- From Python we can export the LIDAR data as PCD (point cloud data) and open the results in MATLAB (using the MATLAB Engine API) for further exploration

The screenshot shows a Jupyter Notebook interface with the following content:

Python 3 (ipykernel)

### Check the data in MATLAB

Initialize the MATLAB Engine

```
[9]: import matlab.engine  
m = matlab.engine.start_matlab("-desktop")
```

### Convert bin files to point cloud files we can use in MATLAB

```
[8]: import os  
import struct  
  
import numpy as np  
from nuscenes.nuscenes import NuScenes  
from nuscenes.utils.data_classes  
  
from urllib.parse import quote as  
import open3d as o3d
```

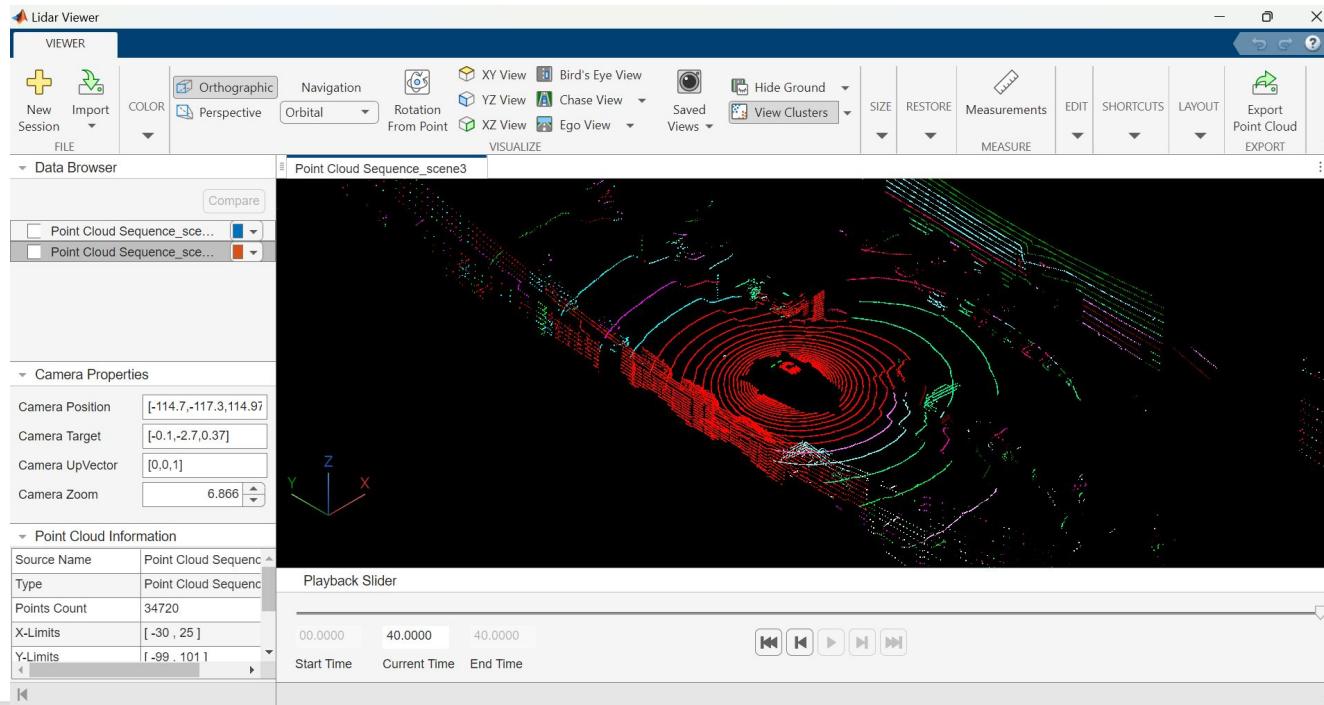
```
[11]: m.lidarViewer
```

```
[11]: <matlab.engine.matlabengine.MatlabFunc at 0x1b82df43ac0>
```



# Next Step: Access LIDAR Data from nuScenes

- From Python we can export the LIDAR data as PCD (point cloud data) and open the results in MATLAB (using the MATLAB Engine API) for further exploration





# Final Thoughts



## Summary

---

Fine-tune an object detection model that demonstrates high accuracy in detecting pedestrians and cyclists

---

Used 15GB of annotated image data from nulimages

---

Had to convert these into XML format in order to use TF records

---

Transfer Learning, object detection model zoo

---

Training on Tufts HPC



## Next Steps: Using the model in MATLAB

- Using the Deep Learning Toolbox, we can now import the trained TensorFlow model into MATLAB
- In MATLAB, use the Lidar Toolbox, Automated Driving Toolbox and Sensor Fusion Toolbox to use both **camera images** and **LIDAR data** from the nuScenes dataset
- This integration with MATLAB would enable a more precise pedestrian detection, as well as getting depth information



# Potential Next Steps

- Using LIDAR and distance data, classify the **safety** of the pedestrians according to how far they are from the car, where they are in relation to the street, etc.
  - Involves neural network to learn **intent** of pedestrians and cyclists
- This open dataset is very comprehensive and can help computer science and engineering students learn more about deep learning and using multiple sensors to make better predictions.



# What We Learned

- Image processing & computer vision
- Deep Learning (both in MATLAB and Python)
- TensorFlow
- Object Detection Models
- XML format (data infrastructure & pipelining)
- Transfer Learning
- HPC
- Teamwork / delegation / collaboration / time management
- Accountability / keeping everyone on the same page
- Working with people from different experience levels



# Questions?

