## Semantic View in Autonomous Driving using Waymo Dataset

Contributors:周禮宏,唐郁秀,紀昕妤,賴煜翔和顏振宇 (sorted by strokes of last name)



#### The Success of Self-driving Vehicle

- Understanding the environment: commonly a 3D semantic HD map at the back-end precisely recorded the environment
- **Self-location**: an on-the-fly self-localization system puts the vehicles accurately inside the 3D world, so that it can plot a path to every target location
- Semantics in the view: a 3D perceptual system detects other moving objects, guidance signs and obstacles on the road, in order to avoid collisions and perform correct actions.



#### **Public Autonomous Driving Datasets**































# Open Dataset

The field of machine learning is changing rapidly.

Waymo is in a unique position to contribute to the research community with one of the largest and most diverse autonomous driving datasets ever released.

#### Access Waymo Open Dataset



Sign in with Google



#### Waymo Open Automated Driving Dataset

- large scale, high quality, diverse dataset
  - from 1,950 driving segments that each span 20 seconds, corresponding to 200,000 frames at 10 Hz per sensor
  - well synchronized and calibrated high quality LiDAR and five front-and-sidefacing camera data
  - captured across a range of urban and suburban geographies
  - labels for four object classes: vehicles, pedestrians, cyclists, and signs
- strong baselines for 2D as well as 3D detection and tracking tasks
  - Data have been annotated with 2D (camera image) and 3D (LiDAR) bounding boxes.

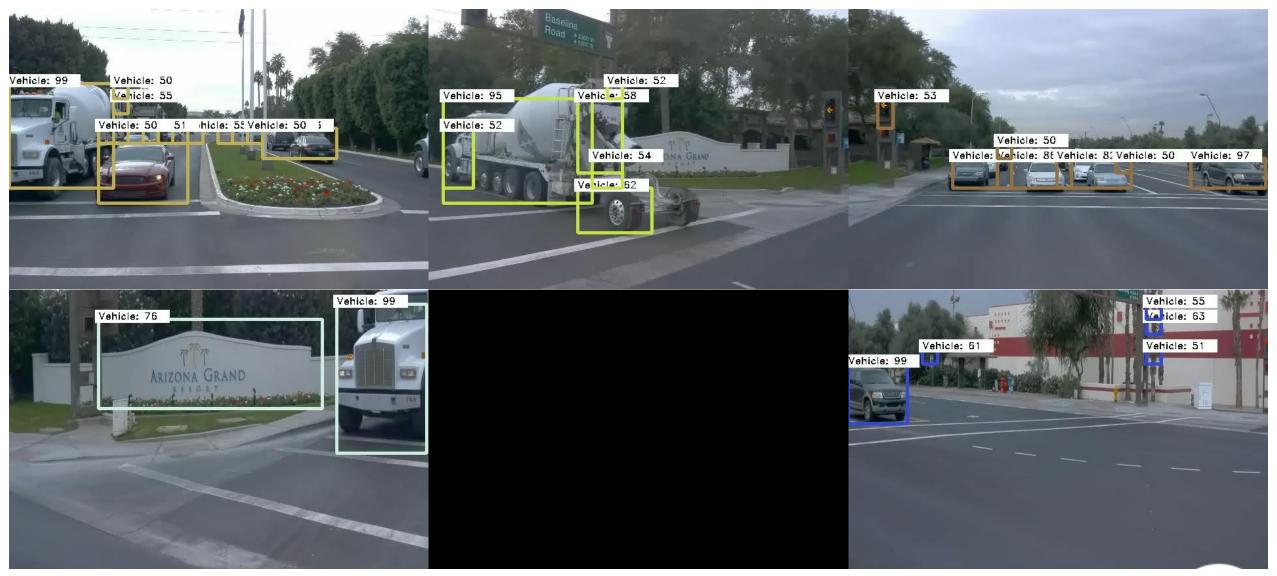


#### Machine Perception Task

#### • Overall:

- Video (or Image): image classification, **object detection**, object tracking (Perez et al., 2017), semantic segmentation as well as instance segmentation(Paszke et al., 2016)
- LiDAR: distance-aware warning
- Specifically for Waymo dataset :
  - driving action prediction (Gu et al., 2020) and data augmentation (Via, 2020)







#### Object Detection in 20 years

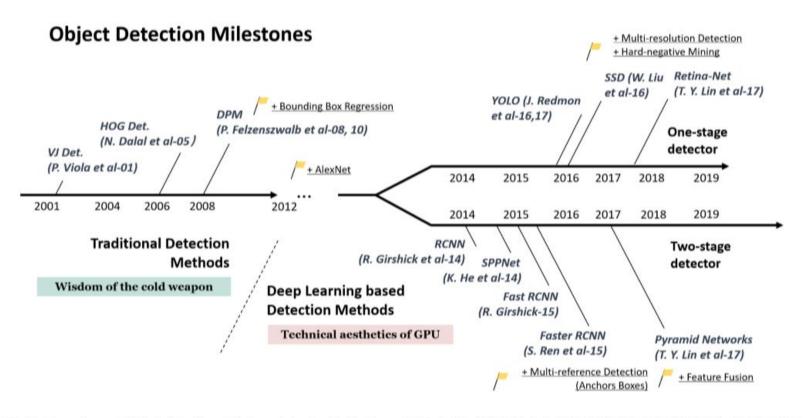


Fig. 2. A road map of object detection. Milestone detectors in this figure: VJ Det. [10, 11], HOG Det. [12], DPM [13–15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20], SSD [21], Pyramid Networks [22], Retina-Net [23].

 Before 2014, traditional methods were to recognize the component.

 After 2014, learning based methods were to represent high-level feature with proposal detection and verification.

Zou et al. (2019)

#### **Objects Detection - Faster R-CNN**

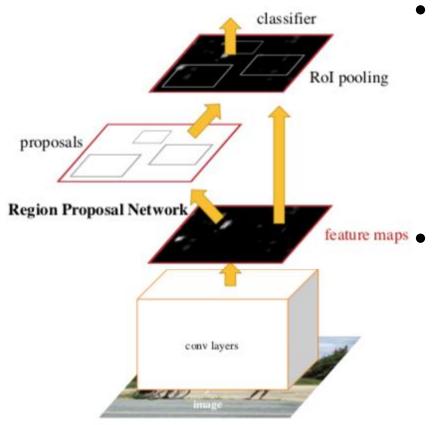


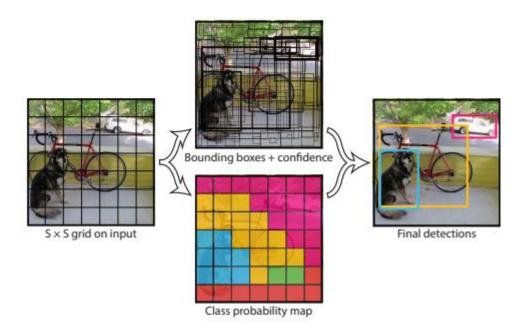
Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

• Fast R-CNN enables end-to-end detector training on shared convolutional features and shows compelling accuracy and speed (Gkioxari et al., 2015).

Faster R-CNN (Ren et al. 2015)

- Deep fully convolutional network that proposes regions
- Fast R-CNN detector that uses the proposed regions.

### Objects Detection - You Only Look Once (YOLO)



**Figure 2:** The Model. Our system models detection as a regression problem. It divides the image into an  $S \times S$  grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an  $S \times S \times (B * 5 + C)$  tensor.

Redmon et al.(2016)

- abandons "proposal detection + verification": Network divides the image into regions and predicts bounding boxes and probabilities for each region simultaneously.
- Drawbacks: YOLO suffers from a drop of the localization accuracy, especially for some small objects, so subsequent versions have paid more attention to this problem (Redmon et al., 2017; Redmon et al., 2018).

#### YOLO V3 10 fps

#### YOLO V3 2.5fps





#### Experiment

• Frequency of frame fetched & increasing scene diversity; for example :

YOLO V3	<b>10 fps</b>	2.5 fps
Number of image (pieces)	990	3780
mAP (%)	1.16	3.57
AP of Pedestrian(%)	0.17	0.01
AP of Vehicle(%)	3.30	7.12
AP of Cyclist(%)	0.01	

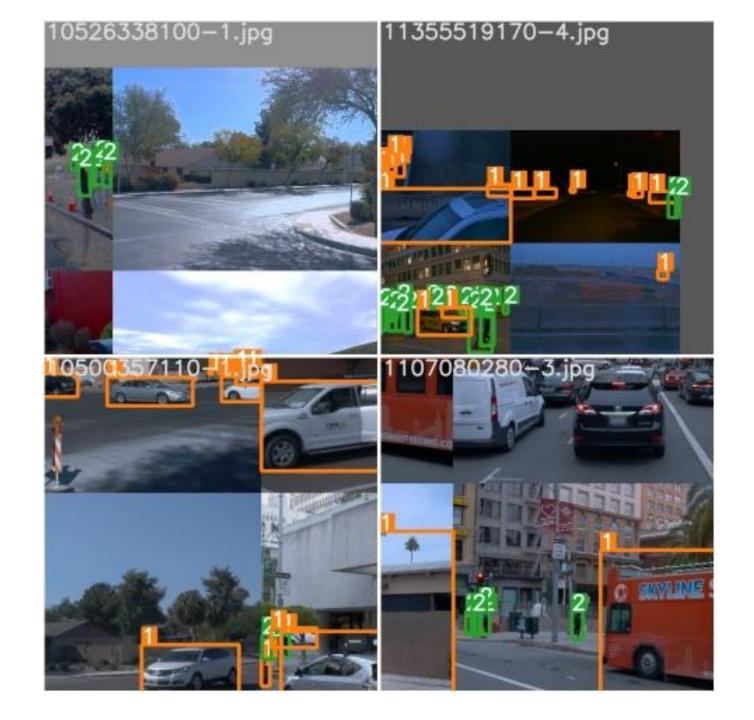
#### YOLO v3 YOLO v4 Faster RCNN

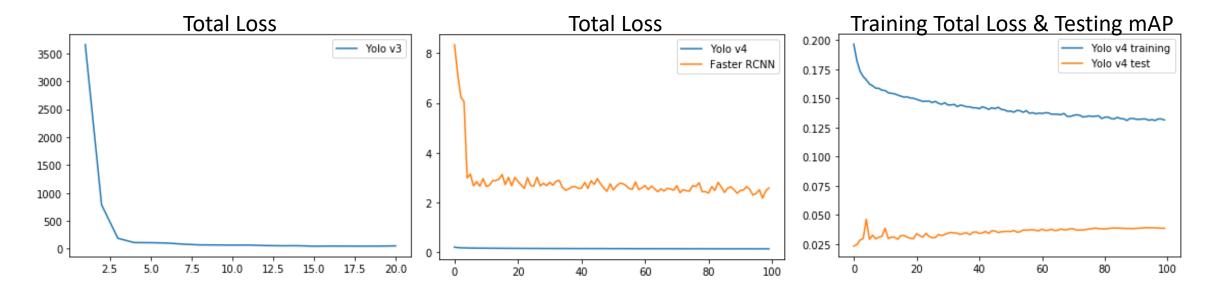




### YOLO v4

Different from YOLO v3





**Long-tailed Learning Model** 

Test Dataset	mAP (%)	AP of CYCLIST(%)	AP of PEDESTRIAN(%)	AP of VEHICLE(%)
Faster - RCNN	48.85		55.7	42.0
YOLO v3	3.56		0.01	7.12
YOLO v4	0.04			

#### Challenge

Version Problem

Test	<b>Python Version</b>	Learning Framework
Faster - RCNN	3.6	TensorFlow-GPU 2.1.0
YOLO v3	3.6	TensorFlow 1.14
YOLO v4	3.7	PyTorch 1.5

Isolated Environment

- Imbalanced Dataset
- Overlapped Region Proposals
- Dataset Diversity and Volume
- Metric Understanding

- Collecting More / Data Augmentation
- Tuning Intersection of Union (IoU)
- Data Enforcement

#### **Thanks**

Contributors:周禮宏,唐郁秀,紀昕妤,賴煜翔和顏振宇 (sorted by strokes of last name)

