Object Detection in an Urban Environment

1. *Project overview*

The main objective is to implement detection of object in an urban environment. The dataset used here is the Waymo Open Dataset. Tensor board is used for displaying the training and evaluation results. Parameters tuning has also been done. The main steps along with implementation details are mentioned below.

2. *Setup*

Step 1 - Exploratory Data Analysis (EDA)

File: Explore data analysis.ipynb

Several steps are performed in EDA on the processes Waymo dataset.

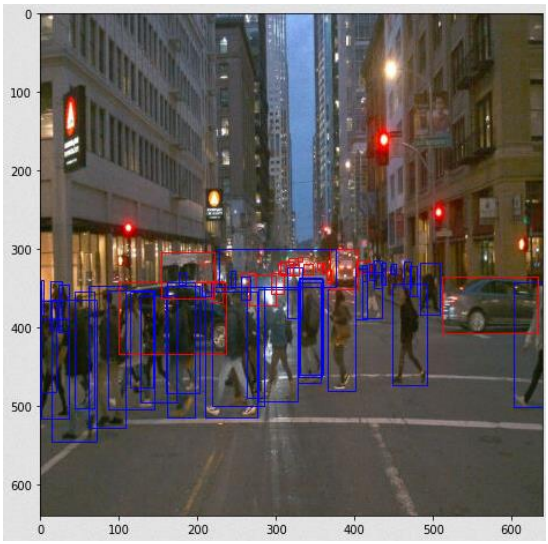
Major steps include

a. Importing libraries for plotting
b. Writing the directory of the source dataset
c. Writing a function to display image and the bounding boxes. For reference, following two images are mentioned here. (Fig 1 and Fig 2)
   (Red bounding box: Vehicles; Blue bounding box: Pedestrian; Green bounding box: Green)
d. Addition EDA is performed to show Object count with respect to Class ID (Fig. 3)
   (Class 1: Vehicles; Class 2: Pedestrian; Class 4: Bicyclist)
   It is observed that the dataset is skewed, i.e. there is an imbalance of classes.

Dataset analysis: The data is divided in three folders namely Train, Val and test. The data is present in TF record format. Different types of images with objects, different weather conditions, dark, bright, different sizes are present.





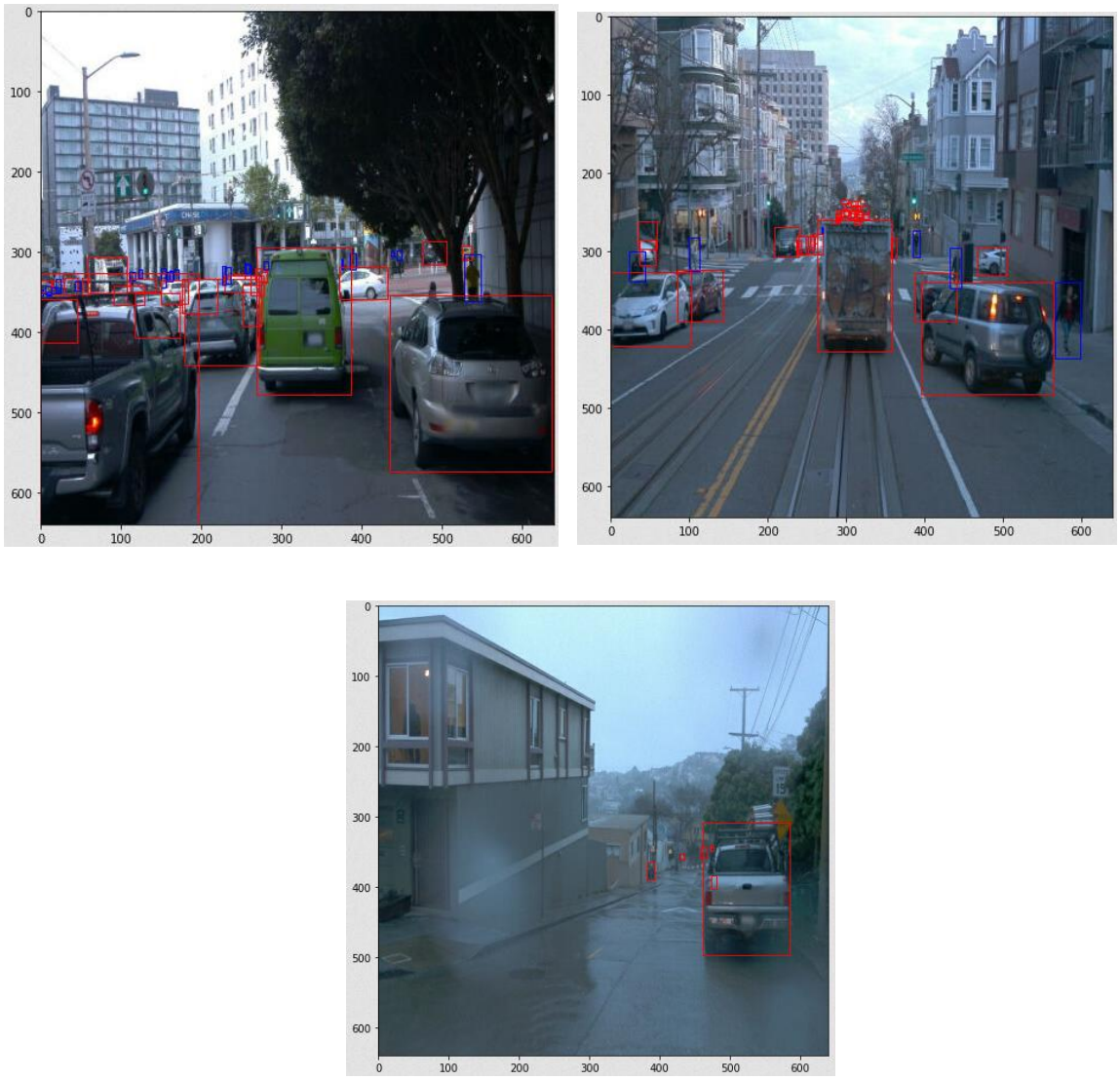


Fig. 1 Images to show the data set (environment, weather and classes distribution)

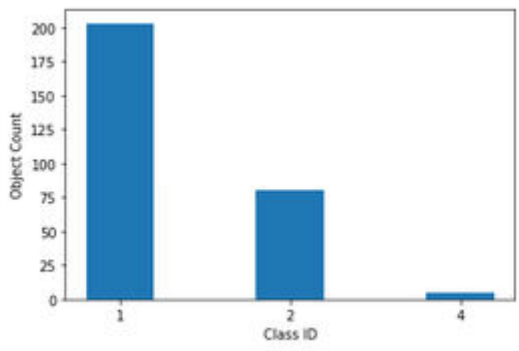


Fig. 2

Step 2 - Edit the config file

File: new_pipeline.config

Before the training, we need to change the config file to change the location of the training and validation files, as well as the location of the label_map file and pretrained weights. A new config file called pipeline_new.config is created and following modifications are done

a. Addition of data augmentation options (brightness, contrast, hue, saturation and color)

b. Changing learning rate base (Old: 0.04, New: 0.0005)
   - ***Reason***: In principle, decreasing the learning rate from a large initial value to a small value allows large weight changes in the beginning of the learning process and small changes or fine-tuning towards the learning process. Therefore, this small value was selected.

c. Changing Total steps (Old: 2500, New: 4500)
   - ***Reason***: To increase the convergence, randomly choose a higher number to increase the steps.

d. Changing warm up learning rate (Old: 0.01, New: 0.0005)
   - ***Reason***: In principle, a lower warm up learning rate means more training time, and hence increasing the ability of the model to predict.

e. Changing warm up steps (Old: 200, New: 300)
   - ***Reason****:* Increasing the warm up steps lead to lowering the learning rate in order to reduce the impact of deviating the model from learning on sudden new data set exposure.

Step 3 - Model Training and Evaluation

The training process was done and Tensor board was used to visualize the training and evaluation graphs. The training and evaluation graphs are mentioned below

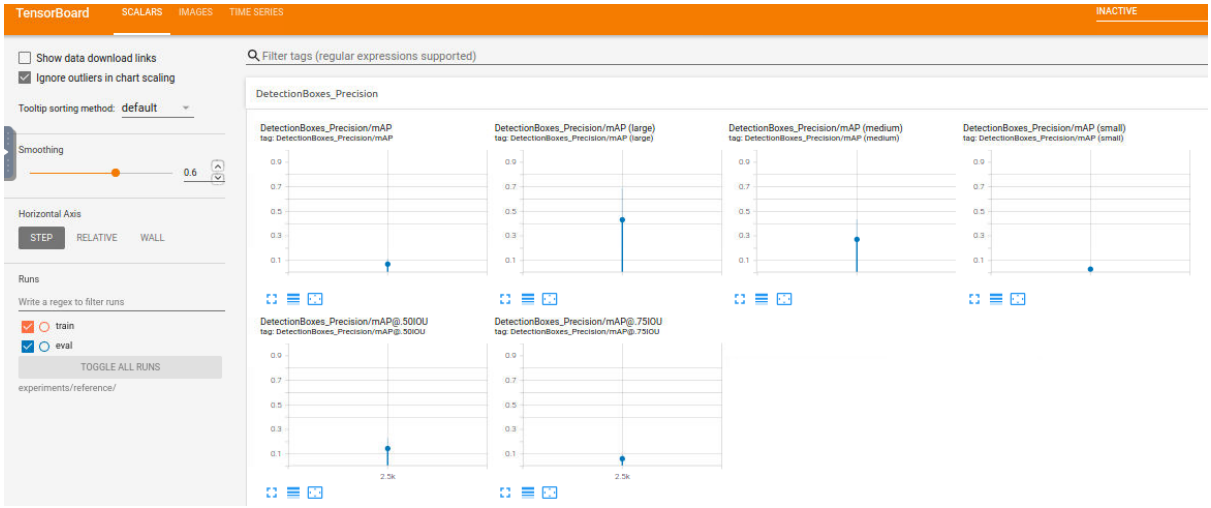


Fig. 4

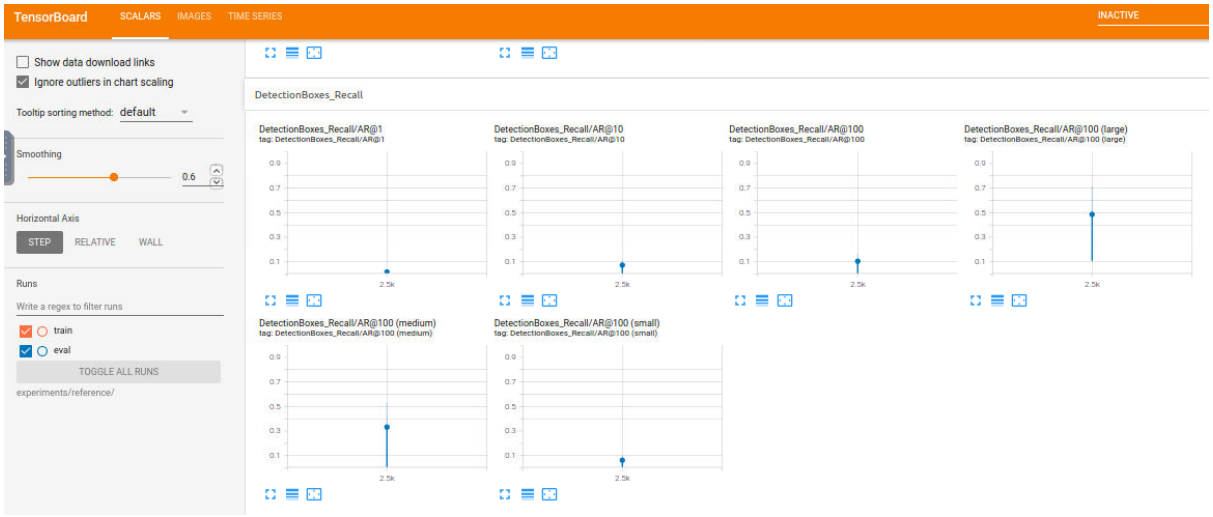
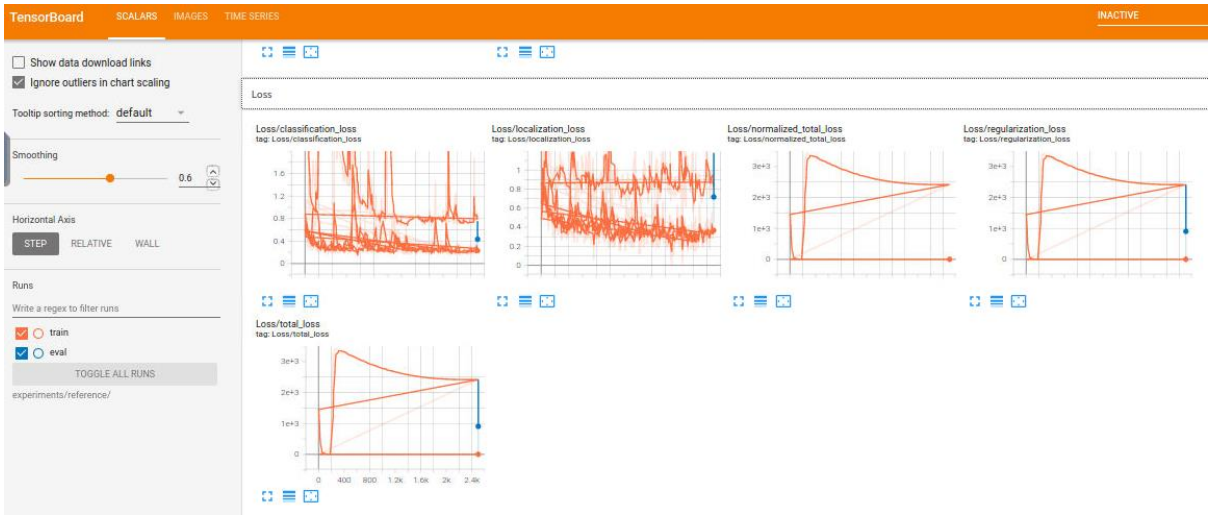

TensorBoard
SCALARS
IMAGES
TIME SERIES
INACTIVE
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
train
eval
TOGGLE ALL RUNS
experiments/reference/
DetectionBoxes_Recall
DetectionBoxes_Recall/AR@1
DetectionBoxes_Recall/AR@10
DetectionBoxes_Recall/AR@100
DetectionBoxes_Recall/AR@100 (large)
DetectionBoxes_Recall/AR@100 (medium)
DetectionBoxes_Recall/AR@100 (small)

Fig. 5


TensorBoard
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Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
train
eval
TOGGLE ALL RUNS
experiments/reference/
Loss
Loss/classification_loss
Loss/localization_loss
Loss/normalized_total_loss
Loss/regularization_loss
Loss/total_loss

Fig. 6


```
root@a440aeb19bd8: /home/workspace 149x32
INFO:tensorflow:Step 1400 per-step time 0.991s loss=0.705
I0311 16:36:14.762388 140512734979904 model_lib_v2.py:682] Step 1400 per-
step time 0.991s loss=0.705
INFO:tensorflow:Step 1500 per-step time 1.006s loss=0.816
I0311 16:37:54.603789 140512734979904 model_lib_v2.py:682] Step 1500 per-
step time 1.006s loss=0.816
INFO:tensorflow:Step 1600 per-step time 0.996s loss=0.799
I0311 16:39:35.479957 140512734979904 model_lib_v2.py:682] Step 1600 per-
step time 0.996s loss=0.799
INFO:tensorflow:Step 1700 per-step time 1.013s loss=0.760
I0311 16:41:15.535774 140512734979904 model_lib_v2.py:682] Step 1700 per-
tep time 1.013s loss=0.760
NFO:tensorflow:Step 1800 per-step time 1.004s loss=0.793
I0311 16:42:55.361418 140512734979904 model_lib_v2.py:682] Step 1800 per-
step time 1.004s loss=0.793
INFO:tensorflow:Step 1900 per-step time 1.005s loss=0.592
I0311 16:44:35.352305 140512734979904 model_lib_v2.py:682] Step 1900 per-
step time 1.005s loss=0.592
INFO:tensorflow:Step 2000 per-step time 1.004s loss=0.849
I0311 16:46:14.891058 140512734979904 model_lib_v2.py:682] Step 2000 per-step time 1.004s loss=0.849
INFO:tensorflow:Step 2100 per-step time 1.012s loss=0.831
I0311 16:47:55.642828 140512734979904 model_lib_v2.py:682] Step 2100 per-step time 1.012s loss=0.831
INFO:tensorflow:Step 2200 per-step time 0.989s loss=0.731
I0311 16:49:35.743353 140512734979904 model_lib_v2.py:682] Step 2200 per-step time 0.989s loss=0.731
INFO:tensorflow:Step 2300 per-step time 1.007s loss=0.703
I0311 16:51:15.419174 140512734979904 model_lib_v2.py:682] Step 2300 per-step time 1.007s loss=0.703
INFO:tensorflow:Step 2400 per-step time 0.997s loss=0.764
I0311 16:52:55.053409 140512734979904 model_lib_v2.py:682] Step 2400 per-step time 0.997s loss=0.764
INFO:tensorflow:Step 2500 per-step time 1.020s loss=0.840
I0311 16:54:34.851697 140512734979904 model_lib_v2.py:682] Step 2500 per-step time 1.020s loss=0.840
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Fig. 7 Training

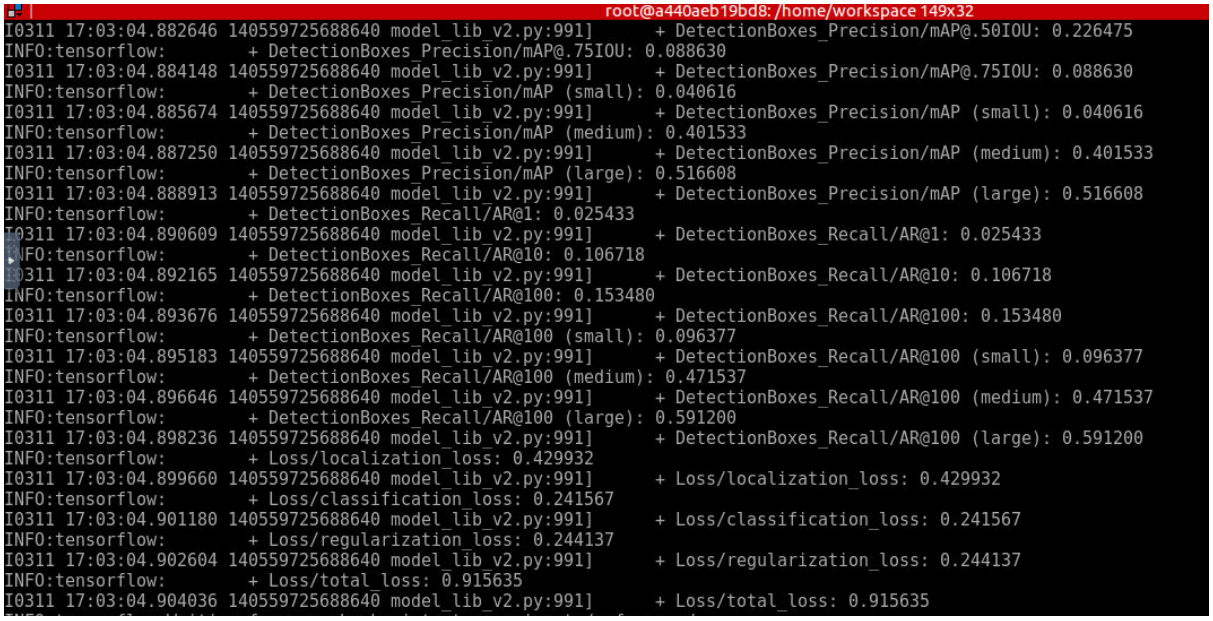

Fig. 8 Evaluation

Step 4 - Improve the performances

File: Augmentations.ipynb

- To improve the performances data augmentation is implemented as mentioned in Step 2
- Also, parameters in Explore augmentations.ipynb has been modified.
- Following augmentation techniques have been used
  a. Random crop image
  b. Random adjust contrast
  c. Random adjust saturation
  d. Random adjust hue
  e. Random adjust brightness
  f. Random distort color

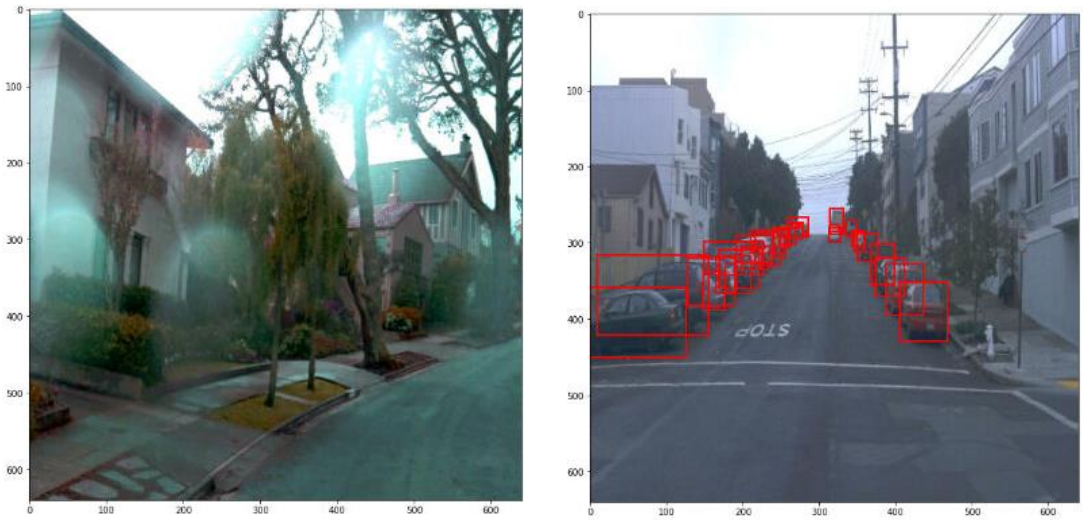

Fig. 9 After augmentation images