Machine Learning Engineer Nanodegree

Capstone Project: Vehicle Detection using Faster R-CNN and DenseNet

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I. Definition

Project Overview

Self-driving cars are finally becoming real. Their impact on people's live and economy will be tremendous [1]. There are so many interesting challenges come with self-driving car technology. One of them is detection of surrounding objects including other vehicles. This information is necessary to make a right decision such as turning without causing any safety problem. My goal is to create a machine learning pipeline for detecting vehicle(s) on a road from a video. The video is captured by a forward looking camera mounted on a vehicle.

There are two main data types used for detecting objects in self-driving car domain:

1) Detecting the objects from images captured by camera. Elon Musk and comma.ai are members of the community believing in this approach.

2) Detecting the objects from point clouds captured using Light Detection and Ranging (LIDAR) technology. Majority of the self-driving car startups bets on LiDar technology such as Waymo.

In this project, I will follow the first approach due to extensive data and benchmark resources.

Detecting an object from an image is one of the main research areas of computer vision. Deformable part models (DPMs) and convolutional neural networks (CNNs) are two widely used distinct approaches. DPM are graphical models (Markov random fields) and use an image scanning technique, such as sliding window approach where the classifier such as SVM is run at evenly spaced locations on the image. CNNs are nonlinear classifiers. CNNs are more popular due to their good performance on object detection [2].

Region-based convolutional neural networks (R-CNN) trains CNNs end-to-end to classify the proposed regions into object categories or background. R-CNN deploys region proposal algorithms (such as EdgeBoxes and Selective Search) to select the region in pre-processing step before running the CNN as classifier. Faster R-CNN uses CNN both for the region proposal and also for the prediction. Google Inception uses Faster R-CNN with ResNet. On the other hand, recently published DenseNet outperforms ResNet. YOLO solves region proposal and associated class probabilities with a single neural network. Single Shot Multibox Detector also accomplishes region proposal generation, feature resampling stage and inference with a single deep neural network. SSD's key feature is the use of multi-scale convolutional bounding box outputs attached to multiple feature sets for prediction. YOLO and Faster R-CNN use single set of feature set for prediction. SSD processing time is shorter than YOLO and Faster R-CNN.

Problem Statement

Vehicle detection is important for public safety and security, surveillance, intelligent traffic control and autonomous driving. Self-driving cars need to identify objects around them such as other vehicles on the road. In this problem, the objects are captured as a video by a forward looking camera mounted on a vehicle. Identification of a vehicle will be important factor in deciding the next action that self-driving car will take such as changing lane. It is a challenging problem due to the large variations in appearance and camera viewpoint, weather, lightening and occlusions. From machine learning perspective, this problem is a classification problem rather than regression. My goal is to differentiate the objects on the road from the background, sky, hill, or road. Then classify if they are vehicle or not. Therefore, combining the object detection model, Faster R-CNN, and the object classification model, DenseNet, helps solving the vehicle detection problem. The output will also be a video similar to the input. However, other vehicles in the video will be shown in box and tracked along the way.

Metrics

I will use average precision (AP) metric. AP is the area under the precision/recall curve. Precision reflects out of all the items labeled as positive, how many truly belong to the positive class. Precision is ratio of true positive instances to the sum of true positive and false positives. Recall reflects out of all the items that are truly positive, how many were correctly classified as positive. Or simply, how many positive items were 'recalled' from the dataset. It is the ratio of true positive instances to the sum of true positives and false negatives.

The reason that I pick average precision: In my model I will query if the object is vehicle or not. I don't have multiple object classes. The precision at every correct point is: how many correct vehicle images have been encountered up to this point (including current) divided by the total images seen up to this point. The reason of not using mean average precision (most used metric in object detection studies) is that I do not multiple object classes hence no multiple queries on the model.

II. Analysis

Data Exploration

Training data for object detection model is annotated images provided by CrowdAI. It contains over 65,000 labels across 9,423 frames (in JPG format) collected from a Point Grey research cameras running at full resolution of 1920x1200 at 2hz. The dataset includes labels for car, truck and pedestrian. I removed the pedestrian label as my goal is not to identify pedestrians but vehicles. Labels.csv retrieved from download link has wrong column order which causes an error during cropping object images. So the column order needs to be changed to x_min, y_min, x_max, y_max, Frame, Label, Preview URL.

Training data for object classification model is the labeled data for vehicle and non-vehicle which are retrieved by Udacity from GTI vehicle image database and the KITTI vision benchmark suite. The data has two classes: vehicle and non-vehicle. There are around 8800 images at each class. The images are 64x64 pixels, in RGB color space with no Alpha channel and in portable network graphics (PNG) format.

Non-vehicle images are extracted from road sequences not containing vehicles. Vehicle images includes high variety of vehicle make, model and color. One important feature affecting the appearance of the vehicle is the position of the vehicle relative to the camera. Therefore, images are separated in four different regions according to the pose: middle/close range in front of the camera, middle/close range in the left, close/middle range in the right, and far range. In addition, the images are extracted in such a way that they do not perfectly fit the contour of the vehicle in order to make the classifier more robust to offsets in the hypothesis generation stage. Instead, some images contain the vehicle loosely (some background is also included in the image), while others only contain the vehicle partially

I made sure that I have equal number of samples from both vehicle and non-vehicle classes. The inputs are randomized before splitting them. %80 of input data is for training while %20 is for validation.

The pipeline will be run on the test video provided by Udacity.

Exploratory Visualization

The sample of labeled images used to train the classification model is shown in Fig1. Theres is good variation of colors, make and point of views in the images.

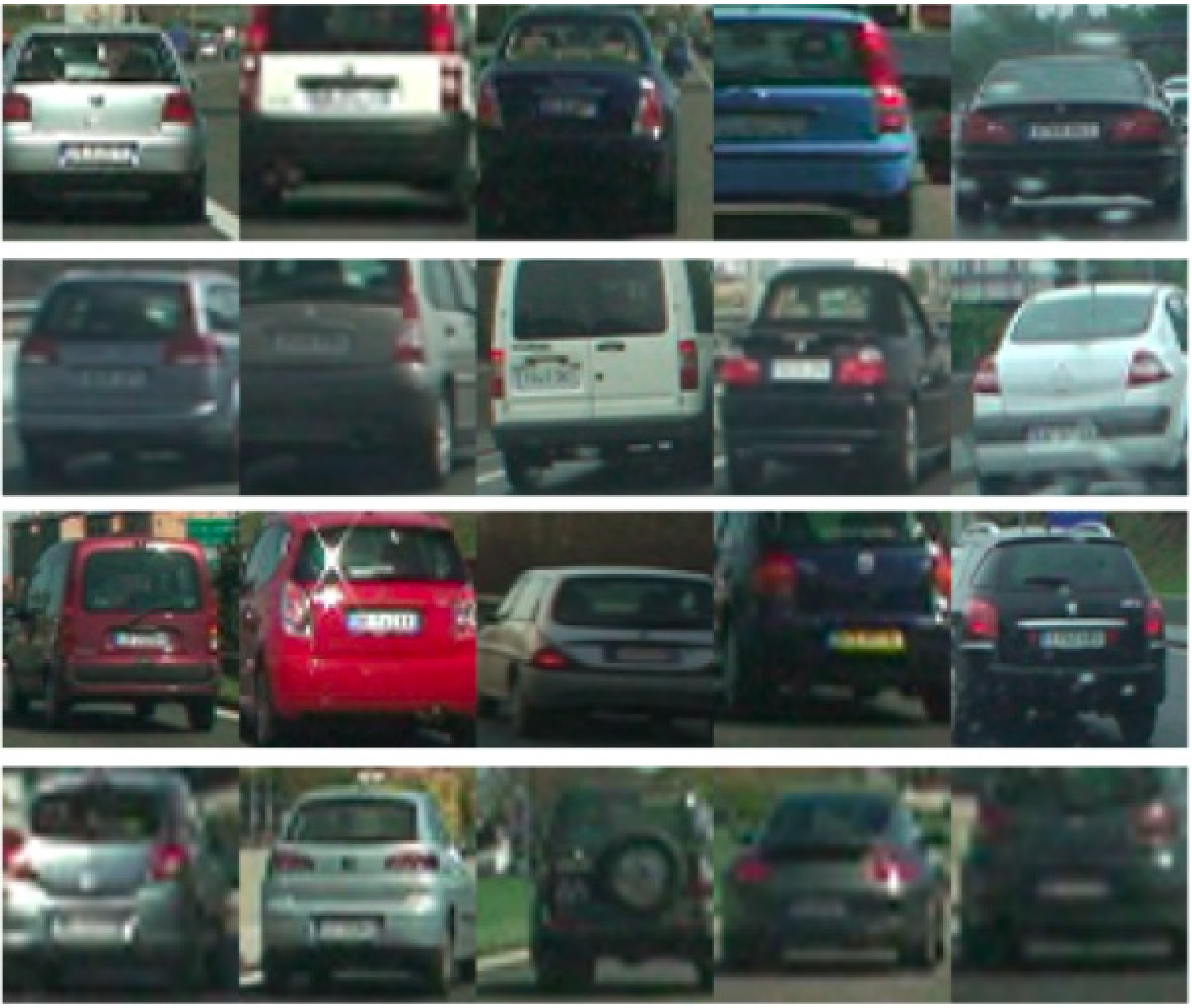
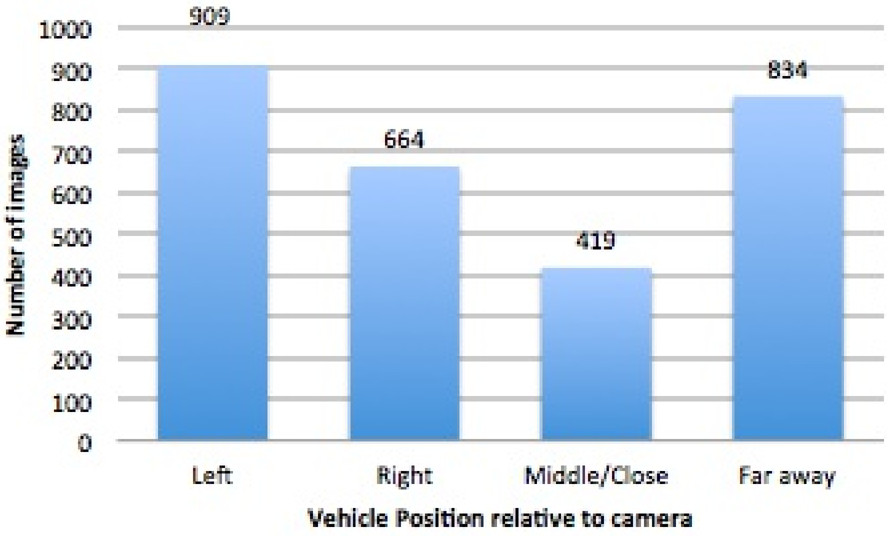


Figure 1: 20 vehicle images taken from GTI

Vehicle position/distance to camera is in varying ranges and not equally distributed as seen in the histogram below. It would be better if they were equally distributed.I won't remove the images to balance the distribution because my goal is to have as many input as possible to train my model. Unfortunately, I don't have distribution of the images retrieved from KITTI that is 5966 images.



Sample annotated image from CrowdAI database that is used for object detection is as follows:

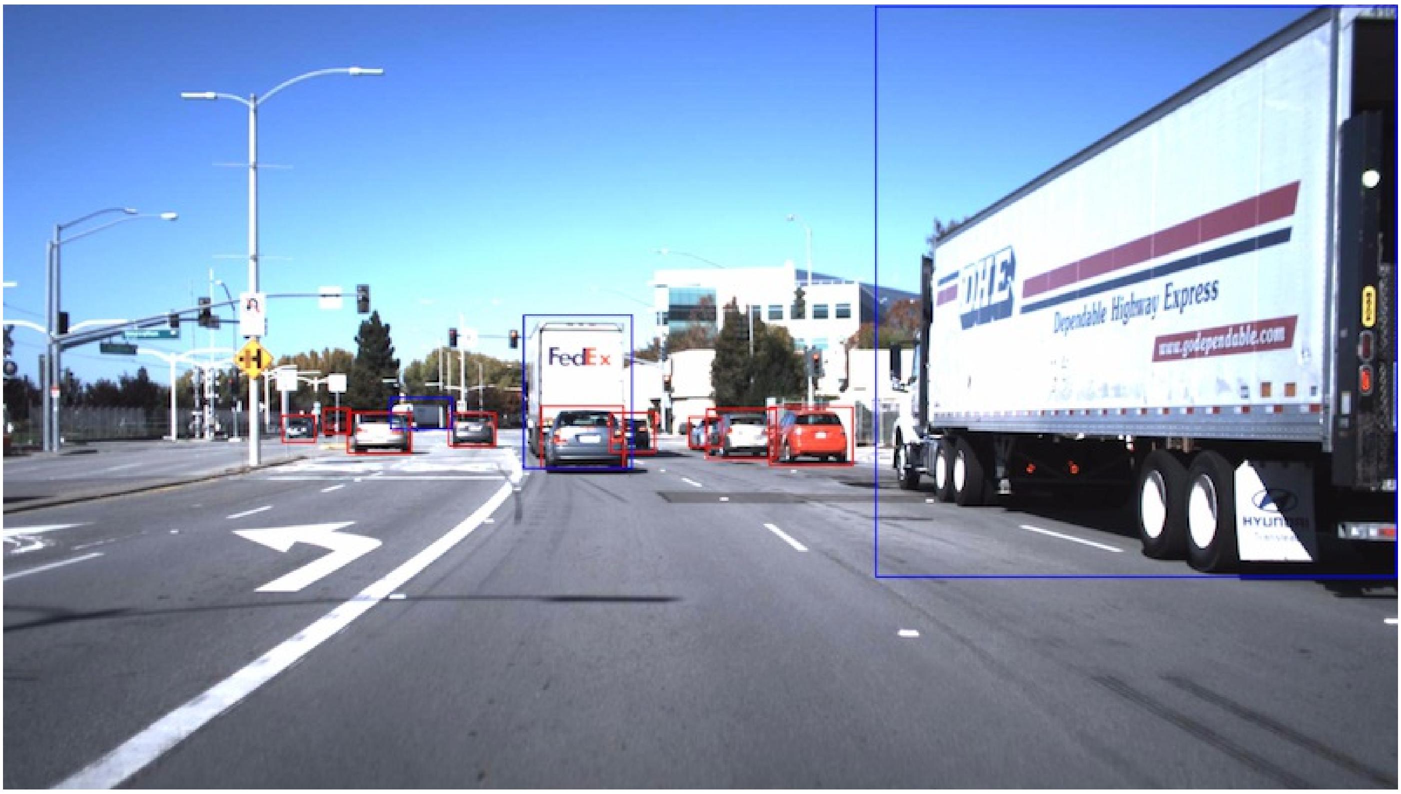
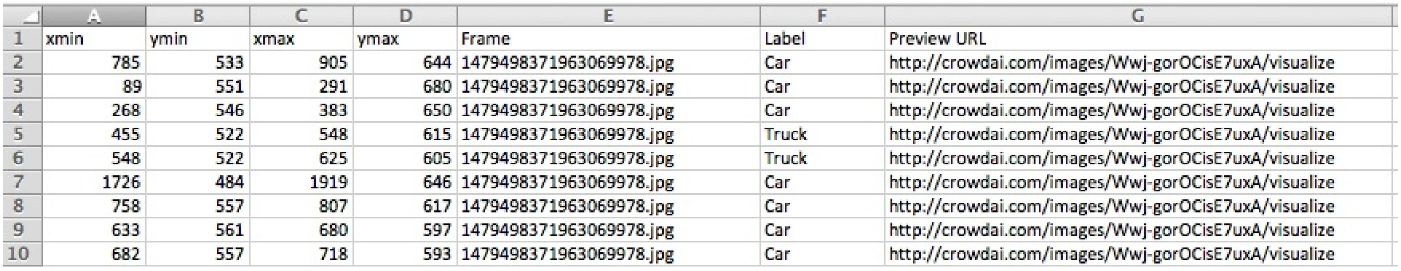


Figure 2: A Sample annotated image from CrowdAI used for training the object detection model.

As seen in Fig. 2, there may be boxes which are well exceeding the object boundaries. See the truck on the left and close to the camera. This may led object detection model to behave the same.

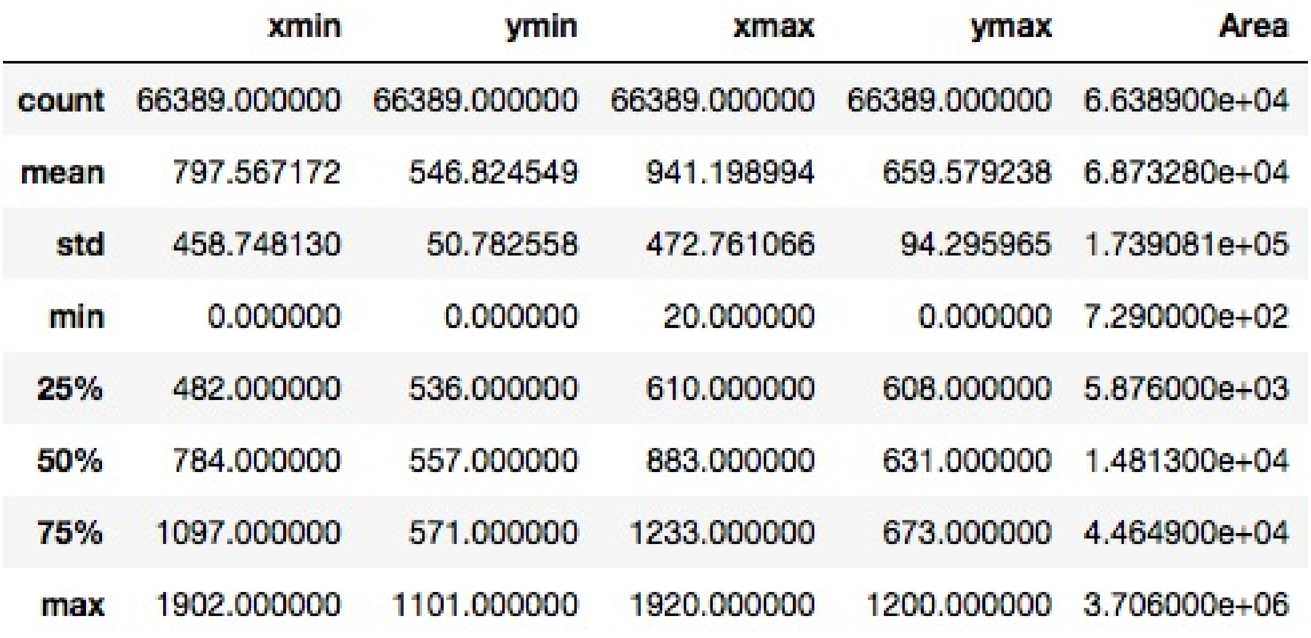
First 10 rows of labels.csv for annotated images is in Fig. 3.



	A	B	C	D	E	F	G
1	xmin	ymin	xmax	ymax	Frame	Label	Preview URL
2	785	533	905	644	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
3	89	551	291	680	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
4	268	546	383	650	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
5	455	522	548	615	1479498371963069978.jpg	Truck	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
6	548	522	625	605	1479498371963069978.jpg	Truck	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
7	1726	484	1919	646	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
8	758	557	807	617	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
9	633	561	680	597	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize
10	682	557	718	593	1479498371963069978.jpg	Car	http://crowdai.com/images/Wwj-gorOCisE7uxA/visualize

Figure 3: First 10 rows of labels.csv.

Fig. 4 provides statistics on 66389 annotations in total - retrieved from labels.csv. I calculated the area of the object boxes (in unit of pixel square). There is high variation of the areas of object boxes which may reflect high variation of the position of the vehicles to the camera or the vehicle size.

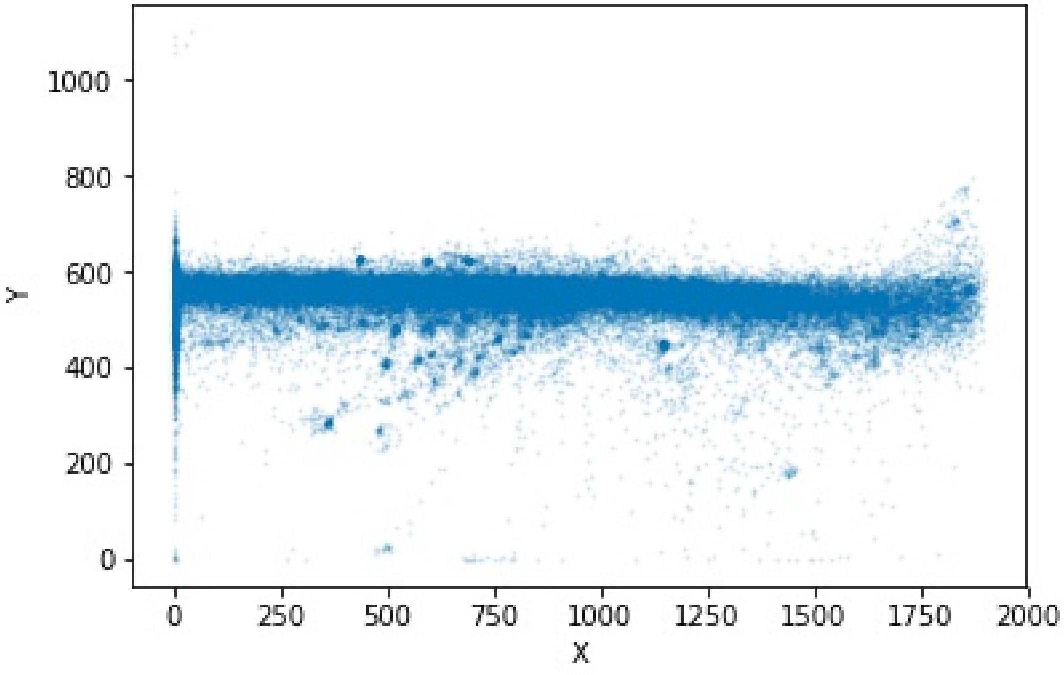


	xmin	ymin	xmax	ymax	Area
count	66389.000000	66389.000000	66389.000000	66389.000000	6.638900e+04
mean	797.567172	546.824549	941.198994	659.579238	6.873280e+04
std	458.748130	50.782558	472.761066	94.295965	1.739081e+05
min	0.000000	0.000000	20.000000	0.000000	7.290000e+02
25%	482.000000	536.000000	610.000000	608.000000	5.876000e+03
50%	784.000000	557.000000	883.000000	631.000000	1.481300e+04
75%	1097.000000	571.000000	1233.000000	673.000000	4.464900e+04
max	1902.000000	1101.000000	1920.000000	1200.000000	3.706000e+06

Figure 4: Statistics of annotations in labels.csv belong to CrowdAI dataset..

Out of 66389 annotations 94.24% of them belong to cars rest is Truck. This reflect the real world scenario where we happen to see cars a lot more compared to Trucks. All these annotations are on 9420 images in total.

All the annotations are positional data. Below I provide a a scatterplot of the bottom-most corner of each annotation. As seen int scatterplot, there are so many annotations that start on the X=0 line. Intuitively, it may mean the pictures taken from a crowded traffic.



Algorithms and Techniques

Faster R-CNN will be used for object region detection. DenseNet will be used for classification if the detected object is a vehicle or not. Both of these models are state-of-the art in object detection and classification. See Domain Background section for details of these models. I will use the pre-trained version of Faster R-CNN and DenseNet because it may take days to train a model from scratch. Faster R-

CNN inception resnetv2 is pre-trained on COCO. DenseNet is pre-trained on ImageNet. COCO and ImageNet are large datasets containing thousands of images for hundreds of object types. Faster R-CNN and DenseNet will go through supervised training with vehicle/non-vehicle dataset that I mentioned above. The images in these data sets will be resized to match the image sizes used during pre-train process. I don't expect to make other pre-processing on the images.

The trained model will be applied to frames of a video. The output of the model will be converted back as video where vehicles bounded with box and tracked along the way.

Benchmark

I use KITTI benchmark suit, that includes performance comparison of models in vehicle detection scenario.The result of Faster R-CNN has already been noted in *

III. Methodology

In my architecture, the object detection model (Faster R-CNN) will be fine-tuned on top of pre-trained weights with annotated custom images. The model returns bunch of object coordinates with confidence scores. The object classification model (DenseNet) will be fine-tuned on top of pre-trained weights with labeled custom images. The model returns a confidence score for an image to belong to any class.

Once our models fine-tuned, they will be fed video frames as shown below

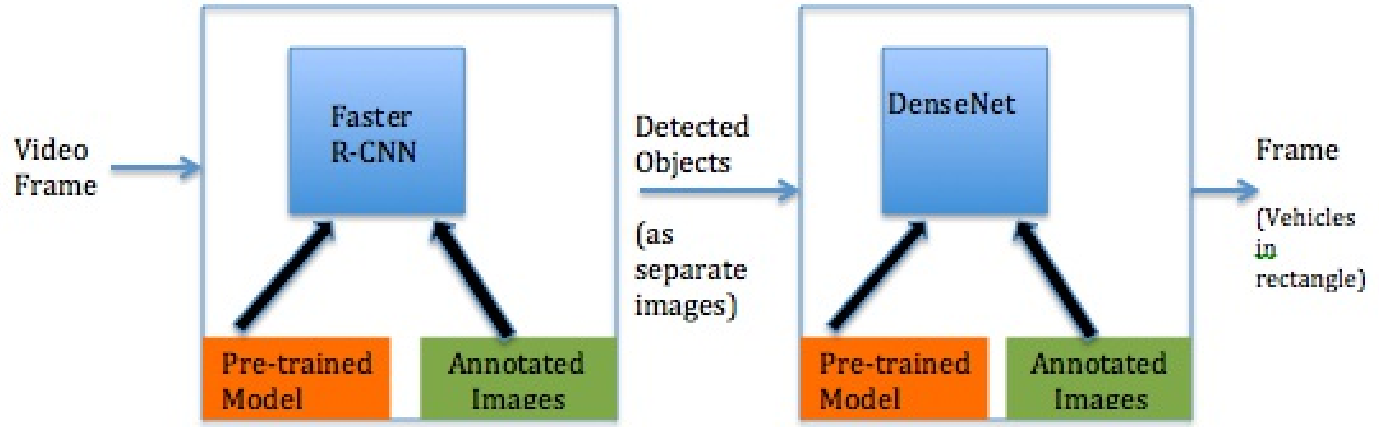


Figure 5: the machine learning pipeline high level view.

For each frame, Faster R-CNN will return at most 100 boxes that represents the coordinates of possible objects. Most of the time, there will be multiple various boxes for one object. Using non max suppression, we decrease the number of boxes. We create a single image from each box representing an object. Each image will be fed into DenseNet for classification. After all the images from a single frame are classified we will re-construct a frame that has vehicle objects boundaries are drawn with rectangle. Later all the constructed frames will be converted to a video.

Data Preprocessing

Processing Data for Object Detection Model

Tensorflow object detection API accepts inputs in the form of tf records. create_tf_record.py converts annotated images in data/annotated_images folder into tf_records. The annotation data comes with the images is labels.csv The order of box coordinates for objects were wrong. I change it as x_min, y_min, x_max, and y_max. I discard objects labeled as pedestrian as my goal is not to detect pedestrians. There are only objects left with two labels left: car and truck. I normalize the box coordinates for each objects. I randomize the inputs before converting them to tf_records. I use 8,000 images to train and 2000 images to validate object detection API performance. I can not use more images due to out of memory or resource exhaustion error at google cloud machine learning engine and google cloud GPU instance. The output is train.record and val.record in data directory. For detailed implementation please see train.ipynb See my guideline

The input images are resized as per the image resizing scheme described in the Faster R-CNN paper. We always resizes an image so that the smaller edge is 600 pixels. If the longer edge is greater than 1024 edges, it resizes such that the longer edge is 1024 pixels. The resulting image always has the same aspect ratio as the input image. See faster_rcnn_gpu.config for details.

Processing Data for Object Classification Model

_load*data* method in densenet.py reads all the images into numpy array. CV2 library reads the images in BGR format. Images are resized to 224x224. Mean pixel of the images are subtracted to make the dataset compatible with the pre-trained models:

img[:, :, :, 0] -= 103.939

img[:, :, :, 1] -= 116.779

img[:, :, :, 2] -= 123.68

All the images are shuffled. %70 of them used for training %30 used for validation.

My classifier is binary classifier, meaning identifies if object is a vehicle or not. The number of classes(or labels) is set to two. Non-vehicle images got class 0 while vehicle images got class 1 tag.

Implementation

Implementing Object Detection Model

I use google Tensorflow object detection api to detect vehicles on image. Tensorflow object detection library already provides training and evaluation scripts. I explained how I used them below. I only wrote code to convert my customer image set into tf records as previously explained in Data Preprocessing Section.

Training an object detection model from scratch requires huge computational resource and time. Therefore, I used the already trained model from Tensorflow Detection Model Zoo I picked faster_rcnn_inception_resnet_v2_atrous_coco which is pre-trained Faster R-CNN inception resnetv2 model. The reason of selecting Faster R-CNN is its high accuracy result.

Tensorflow accepts class labels in pbtxt file. Hence, I create data/label_map.pbtxt as per the instructions here Note that class number has to start from 1.

I need to configure the model before fine-tuning with my own data set. Therefore, I create faster_rcnn_gpu.config. I changed number of classes from 100 to 2. In my case, the classes are car and truck. Then I provided the paths for:

- fine_tune_checkpoint: the directory where you have the pre-trained model.
- input_path: the path for your training record, train.record.
- label_map_path: the path for label_map.pbtxt

I change batch size from 8 to 1 due to memory constraints. The learning rate that I applied is .0003. You can keep the rest of the config file as you retrieved from the sample configuration.

Now, it's time to fine-tune the model with my own data by running the following command from the main directory i.e., ../capstone/

```
python tf_models/object_detection/train.py --logtostderr --
pipeline_config_path=models/faster_rcnn/faster_rcnn_gpu.config --train_dir=models/faster_rcnn/train/
```

I needed to manually stop the training, otherwise it will run 200K steps which was initially used by google to train the model on COCO data set. I had to stop it at ~3K steps due to expensive cloud computing resources and time constraints.

Meanwhile, I run the following command to evaluate the trained model:

```
python tf_models/object_detection/eval.py --logtostderr --
pipeline_config_path=models/faster_rcnn/faster_rcnn_gpu.config --
checkpoint_dir=models/faster_rcnn/train/ --eval_dir=models/faster_rcnn/eval/
```

Few minutes later, run the following command to see the evaluation results on the Tensorboard.

```
tensorboard —logdir models/faster_rcnn/
```

I was satisfied with the result that is total loss of 0.2 and the object detection on the test images. I export a graph from the fine-tuned model to use it in inference phase. I exported graph by running:

```
python tf_models/object_detection/export_inference_graph.py --input_type image_tensor --
pipeline_config_path models/faster_rcnn/faster_rcnn_gpu.config --trained_checkpoint_prefix
models/faster_rcnn/train/model.ckpt-3084 --output_directory models/faster_rcnn/output
```

Remember to give the highest number for model.ckpt in the directory. In my case it was 3084. After successful execution of the command, you should see the following files in models/faster_rcnn/output:

```
tuncer@ins1:~/machine-learning/projects/capstone$ ls -lh models/faster_rcnn/output/

total 465M

-rw-rw-r-- 1 tuncer tuncer 77 Sep 22 02:45 checkpoint

-rw-rw-r-- 1 tuncer tuncer 231M Sep 22 02:45 frozen_inference_graph.pb

-rw-rw-r-- 1 tuncer tuncer 227M Sep 22 02:45 model.ckpt.data-00000-of-00001

-rw-rw-r-- 1 tuncer tuncer 42K Sep 22 02:45 model.ckpt.index

-rw-rw-r-- 1 tuncer tuncer 7.2M Sep 22 02:45 model.ckpt.meta

drwxr-xr-x 3 tuncer tuncer 4.0K Sep 22 02:46 saved_model
```

Now, it is time to do inference on the video frames. I upload the previously trained model using tf.Graph(). See inference.ipynb). When you run the prediction on the model, the output will be boxes that includes coordinates of an object in the form of [y_min, x_min, y_max, x_max]. Keep in mind that the values of coordinates are normalized. For each box, you will see corresponding class value and confidence score for the prediction in classes and scores variables.

The model detects 100 object at max, you can change the value in faster_rcnn_gpu.config file if you want it to be something different. I kept it at 100. As a result, there may be tens of output boxes that by and large show the borders of the same object. Tensorflow has non max suppression method to decrease the number of the boxes. In that method, you can set i) number of output boxes, and ii)iou_threshold. I picked iou_threshold 0.5 and number of output boxes 5. If you have higher values the number of false positives and false negatives may change.

For evaluation of my model, I use Tensorflow object detection api and Tensorboard. See guideline All the steps and commands that I used are documented in train.ipynb and inference.ipynb

Implementing Object Classification Model

I implement DenseNet to classify object as per the DenseNet paper. The model is implemented on Keras using Tensorflow at the back end. The code can be found in densenet.py.

Fig. 6 shows how DenseNet works in high level.

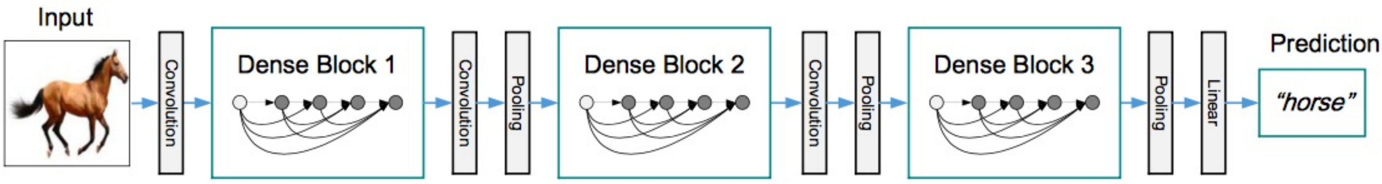


Figure 6: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling. Source.

My DenseNet model uses the following parameters and the corresponding values:

- img_rows:224 (input image width in pixels)
- img_cols: 224 (input image column in pixels)
- color_type: 3 (input image channels. In our case, 3 representing Blue, Green, and Red)
- nb_dense_block: 4 (number of dense blocks to add to end)
- growth_rate: 48 (number of filters to add per dense block)
- nb_filter: 96 (initial number of filters)
- nb_layers = [6, 12, 36, 24] the number of layers of convolution block to append to the model. Note that block id decides which value from the array to be used.
- reduction: 0.5 (reduction factor of transition blocks)
- dropout_rate:0.0 (dropout rate)
- weight_decay:1e-4 (weight decay factor)
- learning_rate:1e-3 (learning rate)
- eps = 1.1e-5 (epsilon for batch normalization)
- classes: 2(number of classes to classify images: vehicle and non-vehicle)
- weights_path: (path to pre-trained weights) I use pre-trained DenseNet on ImageNet for object classification.

In DenseNet model, we have the following methods for each block in Fig 2. Each method uses the above parameter values - if not stated otherwise.

In convolution block method, BatchNormalization, Relu activation, 1x1 Conv2D and 3x3 Conv2D are applied. The method accepts: input tensor, stage (index for dense block), branch (layer index within each dense block), nb_filter, dropout_rate and weight_decay parameters.

In the transition block method, BatchNorm, 1x1 Convolution, averagePooling, optional compression, dropout. I used 1.0 for compression that is to reduce the number of feature maps in the transition block. The method accepts: input tensor, stage, nb_filter, compression, dropout_rate, and weight_decay parameters

In dense block method, the output of each convolution block is fed into subsequent one. The dense block method accepts: input tensor, stage (index for dense block), nb_layers, nb_filter, growth_rate, dropout_rate, weight_decay(1e-4), grow_nb_filters(True, flag to decide to allow number of filters to grow) parameters.

There is helper method to scale the input. The method accepts a set of weights and biases; uses them to scale the input data. The method gets the following inputs:

- axis: integer, axis along which to normalize in mode 0. For instance, if your input tensor has shape (samples, channels, rows, cols), set axis to 1 to normalize per feature map (channels axis).
- momentum: momentum in the computation of the exponential average of the mean and standard deviation of the data, for feature-wise normalization.
- weights: Initialization weights. List of two Numpy arrays, with shapes: `[(input_shape,), (input_shape,)]`
- beta_init: name of initialization function for shift parameter. This parameter is only relevant if you don't

pass a `weights` argument.
- gamma_init: name of initialization function for scale parameter. This parameter is only relevant if you don't pass a `weights` argument.

The implementation is in densenet_custom_layers. In densenet.py you will see this method used as Scale.

The model by default uses data/densenet161_weights_tf.h5 if not provided with weights. I run the model with batch_size 1 and epochs of 10.

I used my own image dataset to fine-tune the model, other than CIFAR dataset. load_data method in densenet.py reads all the images into numpy array. Note that CV2 reads the images in BGR format. Images are resized to 224x224. Mean pixel of the images are subtracted to make the dataset compatible with the pre-trained models:

img[:, :, :, 0] -= 103.939

img[:, :, :, 1] -= 116.779

img[:, :, :, 2] -= 123.68

All the images are shuffled. %70 of them used for training %30 used for validation. My classifier is binary classifier, meaning identifies if object is a vehicle or not. The number of classes is set to two. Non-vehicle images got class 0 while vehicle images got class 1 tag. This is different then what we have done in tensorflow that it requires classes to start from 1, not 0.

See train.ipynb and inference.ipynb for details of my implementation.

For validation of my classification model, I use average precision from sklearn library. It's pretty straight forward, the method accepts valid Y values and predicted values for validation set. The output is a floating number between 0 and 1. Average Precision is closer 1, the better the performance.

Make sure that you are not running object detection and classification models at the same time. Both of the models are using Tensoflow. They try to allocate all the memory in the GPU from the very beginning. Not to face with memory problems, I increased the swap file to 50 GB. The machine I used in Google Cloud is n1-standard-4 (4 vCPUs, 15 GB memory) with 1 GPU that is NVIDIA Tesla K80). It took few hours to train the models.

Refinement

To train object detection API, I was initially thinking to use labeled data (vehicle and non-vehicle which are retrieved by Udacity from GTI vehicle image database and the KITTI vision benchmark suite). I was using only 1K images and giving the edges of each image as object coordinates to the detection model. However, it returned poor performance - meaning the model was not able to detect the vehicle on the test image at all.

Later, I used annotated data set provided by CrowdAI. The new dataset had 630K annotations in total of

9K images. See data exploration section for details. After fine-tuning the model with the new dataset, it was able to detect vehicles on a given test image. See Fig. 3 for a result.

I started first with high number of input images for my detection model. I either got memory or resource exhaustion error. I realized my mistake that I was creating separate tf record for each annotated object on an image. The correct way is to create a tf record that has all the annotated objects on a frame. I started with 1000 annotations that result in 0.4 total loss. Then, I was able to provide the full annotated dataset to the model. This refinement helped me to get total loss of 0.2. On each test image, the model was able to detect all the vehicles with few false positives.

For tensorflow object detection API, I tried different learning rates. The learning rate 0.00001 was resulting 0.5 total loss. I increase the learning rate to 0.0003 that result in total loss of 0.2.

I tried batch size of 128, 64 and 8 but at different stages of the model runs, I faced with problems such as process killed, memory exhaustion etc. Therefore, I used batch size of 1. Disadvantage of having batch size of 1 is high variation in loss value for each step as seen below:

```
INFO:tensorflow:global step 3075: loss = 0.1889 (2.743 sec/step)

INFO:tensorflow:global step 3076: loss = 0.1710 (2.662 sec/step)

INFO:tensorflow:global step 3077: loss = 0.2426 (2.679 sec/step)

INFO:tensorflow:global step 3078: loss = 0.1581 (2.640 sec/step)

INFO:tensorflow:global step 3079: loss = 0.2633 (2.699 sec/step)

INFO:tensorflow:global step 3080: loss = 0.4595 (2.831 sec/step)
```

Tensorflow object detection API returns both object box coordinates on the image and also the predicted class of the image. On top of Tensorflow classification, applying DenseNet classification improves the accuracy ~10%. One significant impact of DenseNet was to eliminate the false positives generated by Faster R-CNN.

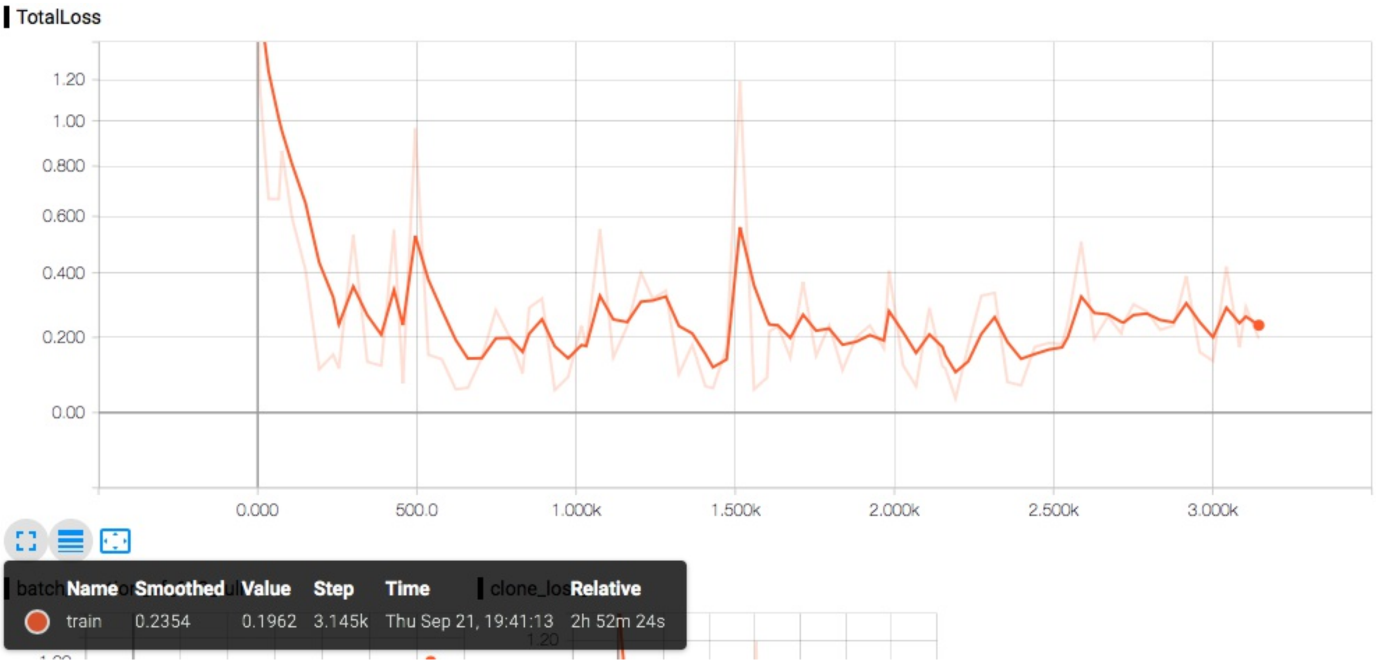
For object classification, I stick to DenseNet model explanation in DenseNet paper as it is a state of the art. I try to train DenseNet with batch size of 64 and 8 and epoch value of 10 but I face with memory problems. Then, I changed batch size to 1 and number of epoch to 10. The DenseNet model successfully ran. I increased the number of epochs to 20 to get better model performance. But the performance difference was not significant at all.

The average precision score of the object classification model is 0.310 when I feed 1K images. The score increased to 0.67 once I used 8.8K images.

IV. Results

Model Evaluation and Validation

I ran my object detection model, Faster R-CNN, about 3K steps with a batch size of 1. See Implementation Section for all the hyperparameters values. The total loss value per steps of running Faster R-CNN is shown in the diagram below.



Name	Smoothed	Value	Step	Time	Relative
train	0.2354	0.1962	3.145k	Thu Sep 21, 19:41:13	2h 52m 24s

Figure 7: Faster R-CNN total loss.

As seen in Fig. 7, the total loss value decreases pretty fast from 1.2 to 0.2 in short time. The reason of this decline is using pre-trained model. Having low total loss is indication of good performance. Note that the model was pre-trained on COCO dataset that also contains vehicle objects. There are hundreds of thousands vehicle instances in COCO dataset - see Fig. 8. The model is originally configured for COCO image dataset. The additional custom image dataset that I used for fine-tuning has only vehicle annotations. Therefore, I did not change much on the configuration rather then batch size and epochs - as explained in Refinement Section. The output of the detection model is set to only two classes: car and truck. Both of these classes are vehicle. So the detection model's sole goal is to detect a vehicle.

Note that Faster R-CNN expects edge of images not less than 600 or higher than 1024 pixels. COCO and my customer datasets fit these size requirements.

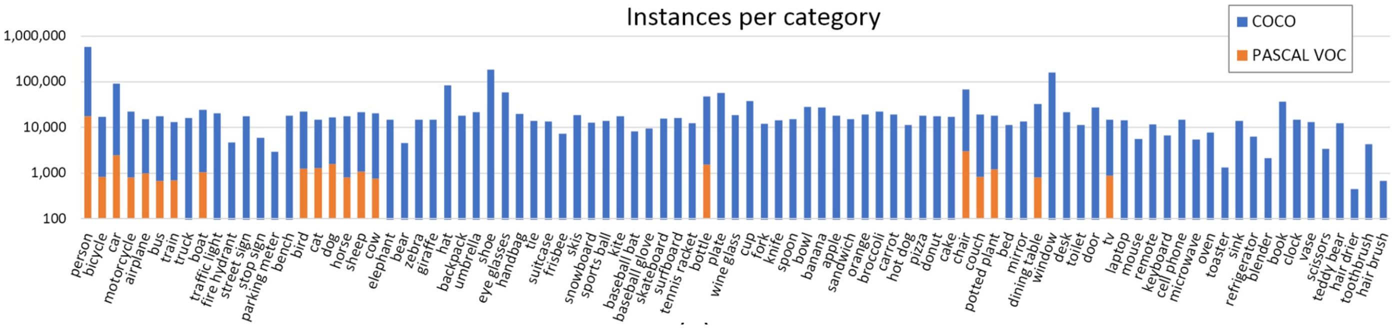


Figure 8: The distribution of the objects per category in COCO dataset. Image Source

I further tested the detection model on different test images. The model was able to detect all the vehicles on the image with few false positives. False positives were some objects on the roadside was detected as vehicle.

I ran my object classification model with 10 epochs and batch size of 1. The final model has average precision score of 0.67839921517. Average precision result can be 1 at highest. In the KITTI benchmark, there are 124 results for car detection is reported, the worst performer's AP score is 2.66% and the best is 90.55%. My model gets the 83th place in the ranking with the AP score of 0.67839921517.

As seen in the output vide 1 and output vide 2, the model detects vehicles with confidence >80%. See the confidence score on the rectangles that show the boundary of the vehicles. When I apply the model on different videos, I got the similar results. Note that my model is not trained on any of the frames from these models.

The built pipeline is combination of both detection and classification models. The object detection model is fine-tuned to only detect vehicles. It returns confidence scores for each object. Then, the classification model does extra filtering on the output of the detection model. Therefore, intuitively I would expect the model perform better than using Faster R-CNN or DenseNet separately. Not having the higher ranking on the competition can be explained by not training the models well. Note that I only used tens of thousands of images, further my batch size and epochs were very limited due to lack of computational resource. Note that the images that my model tested against was not all from KITTI. They are also from GTI. The benchmark results are from state of the art datasets containing hundreds of thousands images with days of training and fine-tuning.

V. Conclusion

Free-Form Visualization

I applied the final model on the video. The output videos can be retrieved from here. See the longer version

As you will see in the video, there are some false positives and false negatives. Tensorflow object detection API returns many object boxes even for the same object. I applied non max suppression. Among many factors, depending on the number of output we would like to get from non max suppression and value for iou_threshold, the number of false positives and false negatives changes.

Reflection

Vehicle detection is important for public safety and security, surveillance, intelligent traffic control and autonomous driving. Self-driving cars need to identify objects around them such as other vehicles on the road. In this problem, the objects are captured as a video by a forward looking camera mounted on a vehicle. I used Tensorflow object detection API for detecting the objects in video frames. Then, DenseNet for classifying the detected objects. Both of the model were pre-trained on large datasets: COCO and ImageNet. Then, I trained the models with vehicle and non-vehicle images. Then applied final models is applied on the test video.

Working on two models: Faster R-CNN and DenseNet required so much effort because, I was executing the whole machine learning cycle (data creation, model creation, tuning, validation/evaluation, saving etc.) two times for each model. This was extremely time consuming. However at the end I learned so many new things and I appreciate the knowledge. This capstone project may be considered just a proof of concept. It helped me to realize how hard it can be to make a production ready system.

The first challenge for me the computing resource related problems: less memory, less CPU etc. I was trying to run the models on my macbook. Then, I tried to use Google Machine Learning Engine. However, I got OOM, out of memory and resource exhaustion errors. I could not find solutions to those problems. Then, I used google cloud platform and GPU instance for the first time. After having few problems related to GPU and SWAP files, I was able to successfully run the models. I realized how computing intensive is dealing with lots of images. Further it also takes great time to compute and slows down progress on the project.

The second challenge for me was reading the input images and converting them into numpy arrays or the format that each model require. I learned few good things about image coloring formats: BGR, RGB, greyscale and alpha channels etc.

The third challenge for me was to limit the number of objects detected by the Tensorflow object detection API. By default it detects at most 100 objects on an image. There may be tens of output boxes that by and large show the borders of the same object. I find out Tensorflow non max suppression method to decrease the number of the boxes. However, depending on the number of output we would like to get from non max suppression and the value of iou_threshold, the number of false positives and false negatives changes.

Improvement

The model can definitely be improved by using at least 2-3 times more image input. I could not use much input resources because of computing resource and time limitations. Further, I could also run training longer. Note that Tensorflow object detection API is fine tuned on pet data in COCO by running the model 200K steps.

The same model can be applied not only vehicles but also traffic lights, pedestrians or other object types as long as you fine-tune with related images. One interesting training would be on car models and years using Stanford AI Cars Dataset.